



HAL
open science

The Financial Cycle and the Business Cycle : it Takes Two to Tango

Guilhem Tabarly

► **To cite this version:**

Guilhem Tabarly. The Financial Cycle and the Business Cycle : it Takes Two to Tango. Economics and Finance. Université Paris sciences et lettres, 2019. English. NNT : 2019PSLED007 . tel-03222421

HAL Id: tel-03222421

<https://theses.hal.science/tel-03222421>

Submitted on 10 May 2021

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

THÈSE DE DOCTORAT

de l'Université de recherche Paris Sciences et Lettres
PSL Research University

Préparée à l'Université Paris-Dauphine

The Financial Cycle and the Business Cycle: It Takes Two to Tango

École doctorale n°543

LABORATOIRE D'ÉCONOMIE DE DAUPHINE (LEDA)

Spécialité SCIENCES ÉCONOMIQUES

Soutenue par **Guilhem TABARLY**
le 23 mai 2019

Dirigée par **Mme Anne Épaulard**

COMPOSITION DU JURY :

M. Michel Aglietta
Université de Paris-X Nanterre
Membre du jury

Mme. Jezabel Couppey-Soubeyran
Université Paris 1 Panthéon-Sorbonne
Membre du jury

Mme. Anne Épaulard
Université Paris Dauphine
Directrice de Thèse

M. Laurent Ferrara
Banque de France
Rapporteur

M. Jean-Paul Renne
HEC Lausanne
Rapporteur

M. Florian Roger
Exane
Membre du jury

Mme. Mariana Rojas Breu
Université Paris Dauphine
Président du jury

Doctoral school 543 : Economics

Ph.D. Thesis

in order to obtain the Ph. D. distinction delivered by

Université Paris Dauphine

prepared and defended publicly by

Guilhem TABARLY

on May 23^d, 2019 at Université Paris Dauphine

**The Financial Cycle and the Business Cycle:
It Takes Two to Tango**

Thesis Advisor : **Anne Épaulard**

Jury

Mr. Michel Aglietta	Examiner	Prof. at Université de Paris-X Nanterre
Mrs. Jezabel Couppey-Soubeyran	Examiner	Prof. at Université Paris 1 Panthéon-Sorbonne
Mrs. Anne Épaulard	PhD supervisor	Prof. at Université Paris Dauphine
Mr. Laurent Ferrara	Reviewer	Economist at Banque de France
Mr. Jean-Paul Renne	Reviewer	Prof. at HEC Lausanne
Mr. Florian Roger	Examiner	Economist at Exane
Mrs. Mariana Rojas Breu	Examiner	Associate Prof. at Université Paris Dauphine

Abstract

The interplay between financial factors and the real economy is now a focal point of macroeconomic research. The introductory chapter seeks to provide a conceptual framework for the study of macro-financial linkages. The rest of the thesis falls within the impetus to research programs brought to the fore by the recent crisis. The second chapter claims that the Financial Cycle is made up of two different components, the Credit Cycle and the Financial Condition Cycle. The two cycles are identified in the light of their impact on economic activity and their relevance is assessed on the grounds of their contribution for the real-time estimation of the output gap. The third chapter uses a data-driven technique to unravel the contemporaneous causal ordering between economic variables and financial variables and investigates the impact of structural financial shocks on economic activity. The final chapter explores, via a battery of econometric and Machine Learning models, whether the inherently unstable nature of financial variables' predictive power for output is related to the modelling framework or to the variables themselves.

Keywords: macro-financial linkages, financial frictions, Financial Cycle, non-linearity, financial Shocks, forecasting, machine learning

Résumé

La thèse explore, via différents outils statistiques, les interactions entre la sphère financière et la sphère réelle, dont la compréhension est cruciale pour assurer la stabilité financière. Le chapitre introductif détaille l'importance des frictions financières pour les mécanismes de transmissions macro-financiers, et illustre ces phénomènes avec la récente crise financière. Le deuxième chapitre décompose le Cycle Financier en deux composantes, le Cycle du Crédit et le Cycle des Conditions Financières. Les deux composantes sont identifiées en fonction de leur impact négatif non-linéaire sur l'activité économique et leur pertinence est évaluée à l'aune de leur contribution à la mesure de l'écart de production en temps réel. Le troisième chapitre étudie l'impact réel d'un choc financier structurel, grâce à une méthode d'identification statistique des liens de causalité entre les variables économiques et financières. Le dernier chapitre interroge les fondements de l'instabilité chronique du contenu prédictif des variables financières à l'aide de nombreux modèles économétriques et d'apprentissage automatique.

Mots clés: liens macro-financiers, frictions financières, Cycle Financier, non-linéarité, chocs financiers, prévision, apprentissage automatique

Remerciements

Quelle sensation étrange que de forcer trois années de travail à s'incarner, statiques, dans un si maigre ouvrage. Ce que ce manuscrit ne dit pas, cependant, c'est en somme tout ce qui compte. En premier lieu l'épreuve que fut pour moi l'écriture d'une thèse. Pour paraphraser Groucho Marx, j'ai passé une excellente année, mais ce n'était pas celle-là. Entreprendre une thèse, c'est chérir le chemin plus que la destination finale. C'est fuir l'azimut, un exercice profondément contre-nature pour quelqu'un qui renâcle à l'idée d'utiliser une carte en montagne. Entreprendre une thèse, c'est aussi songer souvent aux chemins que nous n'avons pas pris. Pourquoi alors entreprendre une thèse en économie ? Ma passion soudaine pour cette discipline est intrinsèquement liée à son imperfection. Un outil théorisé par l'homme et dont il a perdu la mesure. Elle est mouvante, capricieuse, et se métamorphose à chaque fois que l'on tente de l'essentialiser ou d'en extraire une loi. Elle est passionnante uniquement car elle est controversée, chahutée. Elle est propice, plus que toutes les autres sciences, à l'idéologie, et en cela exige de nous une vigilance permanente, au premier chef vis-à-vis de nous-même. Outre l'activité de chercheur, palpitante mais solitaire, j'ai aimé enseigner. D'abord parce que l'enseignement accompagne, voire précède parfois de peu la compréhension du professeur lui-même, mais également car je suis persuadé que l'économie est par essence la science qui ne doit pas être accaparée par ses praticiens.

Plus important encore, ce manuscrit ne dit rien de tous les gens sans qui une seule ligne de cette thèse n'aurait été possible. Que la formule soit consacrée n'ôte rien à sa réalité. Malgré toute la mauvaise volonté dont j'ai fait preuve pour expliquer ma recherche au cours de ces trois années, j'ai été constamment porté par la bienveillance de mes amis, de mes collègues et de ma mère. Être aussi entouré le jour de ma soutenance est sans conteste la plus belle des façons de clôturer une thèse que j'avais justement entreprise comme une reconstruction.

Je remercie tout d'abord Anne et Florian pour leur confiance, puis leur patience. Je remercie ma mère de m'avoir toujours supporté dans mes choix. Je remercie Mathilde, qui m'a sans cesse rappelé que cette thèse était possible quand je n'y croyais plus, déconstruisant à l'envi les excuses destinées à justifier un abandon. Je remercie Irène, Joséphine et Arnaud, Paul, Tran et Mehdi, Florian, Thomas, Théodore, Benoit, Zoé, Clémentine, Louis, Lucie et Flavien, Léa, Walid, Aurélie, Per Yann, Odile et Alexis, Laura et Arthur, Martin, Pierre, Mickael, Hichem, Arthur, Vincent, Mouad, Nicolas, Guillaume, Antoine, Olivier, André-Georges, Bei, Juliette, Caroline à qui je pense souvent, et tant d'autres.

“What’s in store for me in the direction I don’t take?”

Jack Kerouac, *The Subterraneans*

“S’il avait fait tant de sport, m’avait-il expliqué une fois, c’était pour s’abrutir, pour s’empêcher de penser. Il avait réussi: j’étais persuadé qu’il avait réussi à traverser la vie sans jamais ressentir de réelle interrogation sur la condition humaine.”

Michel Houellebecq, *Plateforme*

“La mia indipendenza, che è la mia forza, implica la solitudine, che è la mia debolezza.”

Pier Paolo Pasolini, *Entretiens*

“Casanier, mais fenêtre ouverte sur le monde entier.”

Oxmo Puccino, *Mines de Cristal*

“Voyager, c’est bien utile, ça fait travailler l’imagination. Tout le reste n’est que déception et fatigues. Notre voyage à nous est entièrement imaginaire. Voilà sa force”

Céline, *Voyage au bout de la nuit*

Preamble

“Le capitalisme n’est plus pour la production, qu’il relègue souvent dans la périphérie du tiers monde [...]. C’est un capitalisme de surproduction. Il n’achète plus des matières premières et ne vend plus des produits tout faits : il achète les produits tout faits, ou monte des pièces détachées. Ce qu’il veut vendre, c’est des services, et ce qu’il veut acheter, ce sont des actions. Ce n’est plus un capitalisme pour la production, mais pour le produit, c’est-à-dire pour la vente ou pour le marché. Aussi est-il essentiellement dispersif, et l’usine a cédé la place à l’entreprise. La famille, l’école, l’armée, l’usine ne sont plus des milieux analogiques distincts qui convergent vers un propriétaire, État ou puissance privée, mais les figures chiffrées, déformables et transformables, d’une même entreprise qui n’a plus que des gestionnaires. [...]. Les conquêtes de marché se font par prise de contrôle et non plus par formation de discipline, par fixation des cours plus encore que par abaissement des coûts, par transformation de produit plus que par spécialisation de production [...]. Le service de vente est devenu le centre ou l’âme de l’entreprise. On nous apprend que les entreprises ont une âme, ce qui est bien la nouvelle la plus terrifiante du monde. Le marketing est maintenant l’instrument du contrôle social, et forme la race impudente de nos maîtres. Le contrôle est à court terme et à rotation rapide, mais aussi continu et illimité, tandis que la discipline était de longue durée, infinie et discontinue. L’homme n’est plus l’homme enfermé, mais l’homme endetté.”

Gilles Deleuze, Post-scriptum sur les sociétés de contrôle

Contents

Remerciements	i
	iii
Preamble	v
List of figures	xi
List of tables	xv
Introduction	4
1 Introductory chapter	5
1.1 Introducing finance	5
1.2 The transmission of financial factors to the real economy	7
1.2.1 Neoclassical transmission channels	7
1.2.2 Financial frictions	15
1.3 The ambiguous effect of finance on the macroeconomy	21
1.3.1 Finance and growth	21
1.3.2 The Financial Cycle and Financial Crises	23
1.4 The Global Financial Crisis	28
1.4.1 The structural causes of the crisis	28
1.4.2 The timeline	33
1.4.3 Financial frictions during the crisis	36
2 Halving the Financial Cycle with a non-linear Axe	43
2.1 Introduction	43
2.2 Frequency analysis	44
2.3 The Credit Cycle	46
2.3.1 Data	47
2.3.2 Computing the Credit Cycle	48
2.4 The Financial Condition Cycle	55
2.4.1 Data	59
2.4.2 Computation of the financial factors	62
2.4.3 Construction of the Financial Condition Cycle	66
2.4.4 Results	69

2.5	Are the Financial Cycle sub-components useful for the estimation of the output gap?	73
2.5.1	Introducing the output gap	73
2.5.2	The model	78
2.5.3	Results	81
2.6	Conclusion	84
A	Chapter 2 - Appendix	86
A.1	Different specifications for the simple UCTS model	86
A.2	The Kalman Filter	86
A.2.1	Proof of the Kalman Filter Recursions	86
A.2.2	Maximum Likelihood Estimation of State Space Models	87
A.3	Concordance analysis	89
A.4	Turning points analysis	92
A.5	The Markov-switching model	100
A.6	Estimation of the output gap with individual variables	105
3	What Does a Financial Shock Do? Let the Data Speak for Themselves	107
3.1	Introduction	107
3.2	The data	109
3.3	The model	111
3.4	Results	118
3.5	Conclusion	123
B	Appendix - Chapter 3	125
B.1	IRF for the Mean-Group estimator	125
B.2	Transformed variables	125
B.3	Causal order	134
B.4	Forecast Error Variance Decomposition	136
4	Failing to Predict with Financial Variables: Defending the Case of the Usual Suspect	139
4.1	Introduction	139
4.2	The predictive power of financial variables	140
4.3	The data	143
4.4	The forecasting models	149
4.4.1	The general model	149
4.4.2	The Bayesian Structural Time series model	156
4.4.3	Regularization techniques	157
4.4.4	Decision Tree algorithms	157
4.4.5	Artificial Neural Networks	160
4.5	Forecast Evaluation	163
4.6	Results	165
4.6.1	Forecasting performances	165
4.6.2	Importance analysis	168

4.7 Conclusion	175
C Appendix - Chapter 4	176
C.1 The Minnesota priors	176
C.2 Decomposition of the MSE	177
C.3 Importance analysis	178
C.3.1 Period 1	178
C.3.2 Period 2	184
Conclusion	192
Bibliography	193

List of Figures

1.1	Effect of an Increase in Aggregate Income on Loan Supply and Demand	8
1.2	Effect of a Loosening of Monetary Policy on Interest Rates and Output	9
1.3	Impact of a positive demand shock	10
1.4	A timeline of the GFC through the lens of 4 asset prices	35
2.1	Filtered financial variables	49
2.2	Heatmap of banking crises	50
2.3	Evolution of financial variables around banking crises	51
2.4	AUROC plots for the final model including credit-to-GDP and housing prices	54
2.5	Credit Cycles and cycle component of GDP growth	55
2.6	Correlation between transformed variables	61
2.7	Factors and variance explained	63
2.8	Factor loadings	64
2.9	Smoothed probabilities corresponding to stress regimes and NBER recessions	70
2.10	The Financial Condition Cycle	72
2.11	Posterior draws (post burn-in) for the Credit Cycle	82
2.12	Output gap for the Credit Cycle	82
2.13	Posterior draws (post burn-in) for the Financial Condition Cycle	83
2.14	Output gap with the Financial Condition Cycle	83
2.15	Full sample vs Real time output gap	84
A.1	Belgium	92
A.2	Canada	92
A.3	Denmark	93
A.4	Finland	93
A.5	France	94
A.6	Germany	94
A.7	Ireland	95
A.8	Japan	95
A.9	Netherlands	96
A.10	New-Zealand	96
A.11	Norway	97
A.12	Spain	97
A.13	Sweden	98
A.14	Switzerland	98

A.15 United Kingdom	99
A.16 United States	99
A.17 Smoothed probabilities Factor 1	100
A.18 Smoothed probabilities Factor 2	100
A.19 Smoothed probabilities Factor 3	101
A.20 Smoothed probabilities Factor 4	101
A.21 Smoothed probabilities Factor 5	102
A.22 Smoothed probabilities Factor 6	102
A.23 Smoothed probabilities Factor 7	103
A.24 Smoothed probabilities Factor 8	103
A.25 Residual normality test for Factor 3	104
A.26 Residual normality test for factor 8	104
A.27 Results with credit-to-GDP only	105
A.28 Results with property prices only	106
3.1 IRF for the Pooled estimator	121
B.1 IRF for the Mean-Group estimator	125
B.2 Australia	126
B.3 Belgium	126
B.4 Canada	127
B.5 France	127
B.6 Germany	128
B.7 Ireland	128
B.8 Italy	129
B.9 Japan	129
B.10 Netherlands	130
B.11 New Zealand	130
B.12 Norway	131
B.13 Spain	131
B.14 Sweden	132
B.15 Switzerland	132
B.16 United Kingdom	133
B.17 United States	133
B.18 Forecast Error Variance Decomposition	137
4.1 Transformed variables	147
4.2 Correlation between transformed variables	148
4.3 A simple Regression Tree	158
4.4 A simple Neural Network	160
4.5 Walk-Forward Validation	164
4.6 BSTS importance statistics	170
4.7 Elastic Net importance statistics	171
4.8 Random Forest importance statistics	171

4.9	Neural Network importance statistics	172
4.10	FADL importance statistics	172
4.11	FADL Loadings	173
C.1	BSTS importance statistics	178
C.2	BSTS importance statistics	179
C.3	Elastic Net importance statistics	180
C.4	Elastic Net importance statistics	180
C.5	Elastic Net importance statistics	180
C.6	Random Forest importance statistics	181
C.7	Random Forest importance statistics	181
C.8	Random Forest importance statistics	181
C.9	Neural Network importance statistics	182
C.10	Neural Network importance statistics	182
C.11	Neural Network importance statistics	182
C.12	FADL importance statistics	183
C.13	BSTS importance statistics	184
C.14	BSTS importance statistics	185
C.15	Elastic Net importance statistics	186
C.16	Elastic Net importance statistics	186
C.17	Elastic Net importance statistics	186
C.18	Random Forest importance statistics	187
C.19	Random Forest importance statistics	187
C.20	Random Forest importance statistics	187
C.21	Neural Network importance statistics	188
C.22	Neural Network importance statistics	188
C.23	Neural Network importance statistics	188
C.24	FADL importance statistics	189

List of Tables

2.1	Concordance table	46
2.2	Number of crisis events	50
2.3	Predictive power for banking crises according to AUC	53
2.4	Selected financial variables and data transformation	60
2.5	Top 10 variables with the highest incremental predictive power	65
2.6	Estimation output for \hat{f}_3	71
2.7	Estimation output for \hat{f}_8	71
A.1	Different specifications of the Unobserved Component Time Series Model	86
A.2	Concordance table (1/3)	89
A.3	Concordance table (2/3)	90
A.4	Concordance table (3/3)	91
3.1	P-values for ADF test (H_0 : presence of unit root)	111
3.2	Highest eigenvalues of the companion matrix	119
3.3	P-values for Shapiro-Wilk test (H_0 : the sample is normally distributed)	120
3.4	Recursive ordering implied by the ICA algorithm	120
B.1	Causal structure Lag 0 (1/3)	134
B.2	Causal structure Lag 0 (2/3)	134
B.3	Causal structure Lag 0 (3/3)	135
4.1	Data transformation	145
4.2	P-values for ADF test (H_0 : presence of unit root)	146
4.3	Correlation between Industrial Production growth rate and revisions	149
4.4	Relative Root Mean Square Error	166
4.5	State-dependence of forecast errors	168

Introduction

The interplay between financial factors and the real economy, also known as macro-financial linkages, has been a long-standing focal point of macroeconomic research. While the classical view considered that financial factors were a passive bystander of real factors, recent macro-economic developments challenge such conventional wisdom and suggest that financial factors could significantly amplify the Business Cycle. The breadth and depth of the Global Financial Crisis and the ensuing Great Recession, placed the financial sector center stage in Business Cycle analysis. Consequently, the prominence of financial factors for macroeconomic research is no longer disputed. Recent research programs explore the possibility of financial shocks arising endogenously in the financial sector.

A prerequisite of any analysis of macro-financial linkages, be it empirical or theoretical, is to understand why financial factors have real consequences. To this end, the introductory chapter details the theoretical underpinnings of macro-financial linkages. A central conclusion is that the prominence attached to financial factors depends chiefly on the prevailing degree of financial frictions. In a neoclassical world, with perfect financial markets, macro-financial linkages are confined to the impact of interest rates on expenditure and the quantitative impact of financial factors is dwarfed by the average Business Cycle volatility. Financial flows are channeled directly from savers to borrowers with no active role for financial intermediaries. When financial frictions arise, for instance in the form of asymmetric information between lenders and borrowers, financial intermediaries start to play a specific role and financial factors become a major source of fluctuations for the Business Cycle. Additional frictions, in the form of supply constraints, give an even greater role to financial factors. The study of financial frictions and transmission channels however, falls short of indicating whether the outcome of financial factors will be, on aggregate, positive or negative for economic activity, as these frictions usually play positively as the Business Cycle waxes and negatively as it wanes. We therefore explore the growth-finance nexus literature that describes the inherently ambiguous nature of financial developments for long-term growth. Financial development is found to propel growth up to a certain threshold, from which it starts to fuel financial imbalances and sows the seeds of subsequent financial crises. The introductory chapter then paves the way for the second chapter by reviewing the literature on the cyclical behavior of financial outcomes, defined as the Financial Cycle in analogy to the Business Cycle. This literature complements the broad narratives provided by Minsky and Fisher and highlight the ambiguous role of credit expansion for economic prosperity. Finally, the Global Financial Crisis is used as a natural experiment where financial frictions are pushed to the limit. We first set forth the structural changes of the 1980s, such as the unprecedented wave of financial deepening and

the Great Moderation, two crucial developments which will be extensively referred to in the rest of thesis. We then explain how the crisis propagated from a tiny financial market to the global economy and the sudden transition from a regime of low volatility to heightened financial stress. Finally, we consider the transmission of financial factors to the real economy through the lens of financial frictions.

The rest of the thesis relies heavily on the mechanisms outlined herein and falls within the impetus to research programs brought to the fore by the Global Financial Crisis. The rationale of this research program, which focuses on Business Cycle fluctuations as opposed to movements in secular trends, is threefold. First, macro-financial linkages are investigated in the form of Financial Cycle in research programs that focus on a direct comparison with the Business Cycle. Second, a burgeoning literature focuses on Financial Shocks, whose impact can be interpreted causally in Structural Vector Autoregressive models or Dynamic Stochastic General Equilibrium models. Finally, financial variables have been used as leading indicators anticipating macroeconomic outcomes, on the premise that they have information regarding future economic outcomes embedded in them. The thesis is an attempt to contribute to each of these strands of the literature. The wide recognition that macro-financial linkages should be taken seriously notwithstanding, their statistical measurement is fraught with pitfalls, owing to the elusive nature of financial factors and their simultaneity with real factors. The thesis addresses this issue via the use of state-of-the-art statistical techniques suited to the multi-faceted aspect of financial factors.

While the definition of the Business Cycle is now well-established, the jury is still out on which variables should be used as a proxy for the Financial Cycle. To this end, the second chapter argues that the Financial Cycle should be decomposed into two different interacting components, a low-frequency, quantity-based cycle, and a short to medium-term component, that we define as the Credit Cycle and the Financial Condition Cycle respectively. Instead of computing these cycles first and estimating their relationship with economic activity afterwards, they are identified in the light of their impact on economic activity at specific frequencies. Because estimates of the unconditional impact of financial factors on economic activity have been found to be small or inconclusive, the two sub-cycles are identified in states of the world where financial frictions are supposed to bind more, and to weigh on economic activity more significantly. This is carried out for identification purpose only and does not necessarily imply that financial factors necessarily weigh on the economy. The construction of the low-frequency cycle bears upon its predictive power for financial crisis. The high-frequency component, is computed by aggregating a large number of financial variables via data-reduction techniques, then selecting the financial factors that affect output in financial stress episodes, defined endogenously via a regime-switching model. The relevance of the two estimated Financial Cycles is then assessed by measuring their respective contributions to the real-time estimation of the output gap. We show that the two components are helpful for the real-time estimation of the output gap. Moreover, the Credit Cycle incorporates insightful information about the build-up of macroeconomic imbalances. Our results suggest that the Financial Cycle could be used as a substitute to standard variables, like inflation or

fiscal balances, that may have lost relevance to pin down the state of the economy in real-time.

The third chapter complements the findings outlined herein with a more structural analysis, whereby correlations can be interpreted causally. The chapter aims to quantify the impact of financial shocks on output via a Structural Vector Autoregressive model, which allows to take into account the two-way interactions between financial and economic factors. Financial shocks are defined as unexpected and exogenous impulses on credit quantities, housing prices and equity prices, on the premise that these variables capture the gist of macro-financial linkages. New-Keynesian models usually provide theoretical underpinnings for the identification restrictions in Structural VAR models. These models, however, are relatively silent when several financial variables are included. As a result, the VAR literature that identifies financial shocks recursively usually resorts to restrictions based on intuition. This is problematic as economic interpretation of such VAR typically hinges crucially on the choice on the recursive ordering. In this respect, we employ a data-driven technique called Independent Component Analysis in order to unravel the contemporaneous causal ordering underlying the relationship between inflation, output, the policy rate and our set of financial variables. Under the assumption of contemporaneous acyclicity, the technique exploits the non-gaussianity of the residuals to uniquely pin down the mixing matrix that relates structural shocks and reduced-form residuals. The ordering between economic and financial variables is found to be fairly stable across developed countries, but different from what is usually assumed by the literature, which warrants the choice of a data-driven procedure ex-post. We find that a positive exogenous impulse on financial variables increases output between 8 and 15 quarters. Additionally, the results provide evidence of financial accelerator mechanisms at play.

The fourth and final chapter follows in the footsteps of a long line of studies that explore the predictive power of financial variables for future economic prospects. While theoretically lower macroeconomic volatility, clearer central bank communication and financial innovation should have reinforced the economic content of financial variable, their predictive power is found to be highly unstable and elusive. The aim of this chapter is to understand whether this is related to modelling choices or to the variables themselves. We first assess the short-run predictive power of a set of financial variables, whose selection is grounded on theoretical underpinnings. Forecasting performances are evaluated on the basis of an appraisal of the strengths and weaknesses of a battery of forecasting models. Instead of performing a horse-race between competing models, we use the characteristics of each model to better understand why financial variables may or may not anticipate the Business Cycle. These characteristics include data reduction, shrinkage, variable selection or non-linearity. We also assess the relative importance of financial variables in each model to further hone our understanding of the mechanisms underlying the predictive power of financial variables. Overall, the results confirm that financial variables have lost relevance over the recent period. However, financial variables should not be systematically discarded and more flexible forecasting models should instead be considered to make the most of their information content.

Turning to the policy implications, the thesis suggests that financial stability requires a

close supervision of financial factors. To this end, timely measures of the Financial Cycle fluctuations are key to mitigate its amplifying and potentially destabilizing role. In this respect, macroeconomic research should benefit from the broad-based expansion of financial data brought about by the Global Financial Crisis. Once the dust has settled, however, it takes purposeful analysis to turn a large amount of financial data into relevant input for early-warning or forecasting models.

Chapter 1

Introductory chapter

“They [economists] turned a blind eye to the limitations of human rationality that often lead to bubbles and busts, [...] to the imperfections of markets - especially financial markets - that can cause the economy’s operating system to undergo sudden, unpredictable crashes.”

Paul Krugman (2009)

“Hello, Paul, where have you been for the last 30 years? Pretty much all we have been doing for 30 years is introducing flaws, frictions and new behaviors”

John H. Cochrane (2011)

“Without finance, macroeconomic models are like Hamlet without the prince”

Claudio Borio (2015)

1.1 Introducing finance

Finance exists because some agents have a need for external financing, while other have the capacity and the willingness to save. The need for external financing arises from a discrepancy between the sources of funds, in the form of disposable income for households, cash flows for firms, deposits adjusted for reserve requirement and loan repayments for banks and tax receipt for the government, and the need for spending, pay back debt or accumulating financial securities. The rationale of financial assets, be it under the form of a piece of ownership or a debt contract, is therefore to trade intertemporal claims to smooth spending over time, or intratemporal claims to insure against idiosyncratic risk. Finance can thereby be understood as a way to transfer wealth from one state to the other, or forward and backward across time. Smoothing across different state of the world, for instance in the face of variable income, is a way to lessen the sensitivity of agents to fluctuations in income. Intertemporal

smoothing allows households to consume without current income and firms to invest without accumulating profits beforehand when profit is by definition low because of a lack of initial investment. Finance enables to reimburse when the agent is richer, having accumulated productive or human capital. In the Overlapping Generation model (Samuelson [1956]), for instance, agents have finite life span and are financially-constrained in their early times, and debt securities allow them to transfer saving across generations. The youngest generation borrow money, only constrained by their future reimbursement capacity, from the working generation that is saving for retirement. The oldest generation consume all its income and sell-off its assets.

Perfect smoothing however requires complete markets, in the sense that there exist contingent claims, in the form of insurance of investment, that span every possible state of the world, such that agents can insure against any event (Arrow [1964]; Debreu [1959]). Market completeness is a necessary condition of the first fundamental theorem of welfare¹ (Arrow and Debreu [1954]). Market incompleteness, on the contrary, sets limits to the feasible range of intertemporal and intratemporal trades and precludes risk-sharing, as agents are unable to anticipate or postpone spending and to insure against uncertain events. For instance, in the Overlapping Generation model, the sequential structure of the model limits the trading opportunities between agents born later and agents born earlier and yields a Pareto suboptimal equilibrium. Market incompleteness typically arises because of agency problems and information asymmetry, whereby the lender cannot enforce the contractual obligations of the borrower, or owing to a limited capacity to borrow against human capital.

Market completeness, however, is not enough to generate non-zero financial flows. If agents are homogeneous, there is no reason for them to trade. Heterogeneity may arise because agents are ex-ante identical but subject to random idiosyncratic shocks or endowments, because of differences in technology or preferences, or owing to different discount rates. When heterogeneity arises, financial flows improve welfare by allocating funds to agents that need it the most. Productive agents hold most of the productive capital and issue claims to the less productive ones. In the words of Bagehot [1873], “*capital runs as surely and instantly where it is most wanted, and where there is most to be made of it*”. At the global level, the development of international capital markets helped to funnel capital from countries with a surplus of savings towards those with a surplus of investment opportunities.

In practice, owing to market imperfections, financial intermediation is performed via the financial sector and in its most basic form, the banking sector. The first key role played by the banking sector is to structure loans with the desired duration and liquidity (Diamond and Dybvig [1983]; Holmstrom and Tirole [1997]), usually by borrowing short and lending long. Short-term savings are transformed into deposits while long-term savings are transformed to stocks and bonds, via the intermediation of asset management firms such as pension funds or insurance companies. Banks also have special skills for screening, monitoring and assess-

¹The first fundamental theorem of welfare states that any competitive equilibrium leads to a Pareto efficient allocation of resources.

ing borrowers reimbursement capacity (Holmstrom and Tirole [1998]). Finally, the banking sector generates nominal purchasing power in the form of money creation. Money consists of the currency issued by the central bank plus the liabilities of the banking sector in the form of demand deposits. The lion's share of money is thereby being created by commercial banks extending loans. This ability to create money is constrained by reserve and capital requirements. The former serves as a deposit insurance against the risk related to the maturity mismatch, while the latter is a safeguard against unsustainable levels of leverage to protect banks against solvency risk. In this bank-based environment, the central bank exerts control over the monetary base, i.e. currency plus banks reserves, via the impact of the policy rate on reserves and subsequently on credit.

Financial intermediation should however not be restricted to bank lending. Corporate funding resources can also be allocated in the form of bond lending or equity investment. The optimal financing choice between bank-based or market-based credit and public or private capital, will depend on the characteristics of the firm, in terms of maturity and cash-flow generation. The financial sector can be further decomposed into the primary market, that deals with the issuance of securities and directly influences the investment decision of the firm and the secondary market, where securities are traded without direct feedback for the firm. The price discovery process that takes place in the secondary market is a key determinant of funding conditions on the primary market and serves as a gauge for risk-aversion and expectations about future outcomes. The financial sector also performs other services than the sole channelling of financial flows from savers to borrowers².

1.2 The transmission of financial factors to the real economy

1.2.1 Neoclassical transmission channels

In a world with perfect financial markets, financial factors are a mere reflection of macroeconomic outcomes and do not play a first-order role in economic fluctuations. Perfect financial markets assume complete markets, instant clearing, no transaction or bankruptcy cost and no information asymmetry. Under these conditions, the theorem of Modigliani-Miller (Modigliani and Miller [1958]) states that the market value of a firm is independent of its financial structure, which entails that firm's real decisions such as investment are solely motivated by the maximization of shareholders' claims. Internal resources such as cash flows do not affect investment as the firm perceives the opportunity cost of internal funds to be the market interest rate. The Modigliani-Miller theorem also explains why debt should not necessarily be preferred to equity even if the cost of debt is typically lower than the cost of equity as investors demand an additional rate of return to compensate the fact that their equity is now riskier, which increases the weighted average cost of financing to the same extent than if the company had issued equity instead. The Modigliani-Miller theorem fails for instance

²Levine [2005] defines five key economic features of the financial sector: 1) Providing information about investment opportunities and the allocation of capital; 2) mobilization and pooling of household savings; 3) monitoring of investment; 4) financing trade and consumption; 5) operating secondary markets through liquidity provision and risk management such as diversification and hedging.

when distortions make debt more advantageous than equity. A typical distortion in developed countries is that debt is tax-advantaged because interest is paid out of before-tax earnings while dividends are paid out of after-tax earnings, even accounting for income taxes paid by investors on dividends.

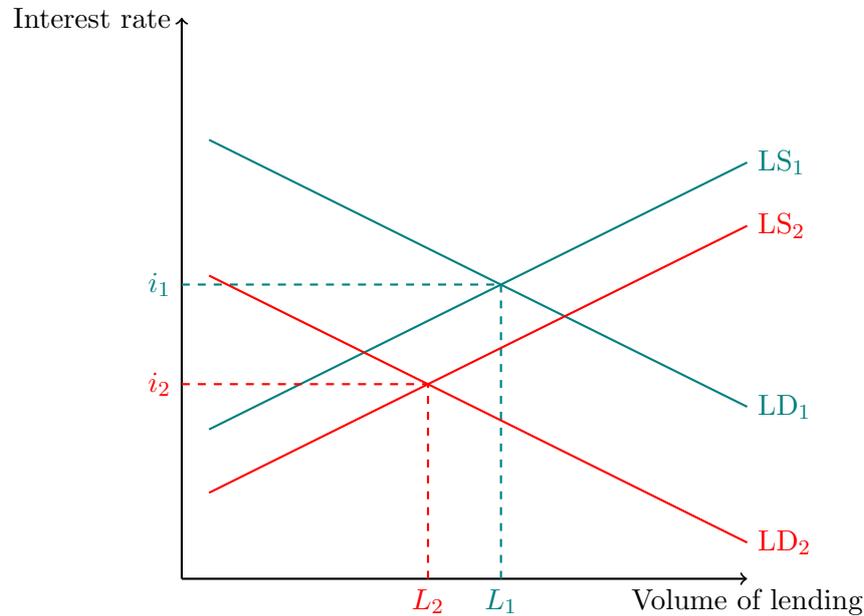


Figure 1.1: Effect of an Increase in Aggregate Income on Loan Supply and Demand

At the macro-level, perfect financial markets imply that funds will always flow to the most profitable project or to agents that value them the most. Asset prices are fully determined by aggregate demand and supply forces on the economic side. In the words of [Robinson \[1952\]](#), “*where enterprise leads, finance follows*”. This does not mean, however, that financial factors have no impact on economic activity. The main channel of transmission occurs through the impact of interest rates on investment and consumption. Consider a simple model where the financial sector consists in a frictionless lending market. The Loan Supply (LS) schedule corresponds to the amount of lending that savers are willing to provide (by delaying current consumption) as a function of the interest rate, which is the opportunity cost of holding money. Likewise, the Demand for Loans (LD) is downward sloping and corresponds to the volume of loans demanded for a specific interest rate. The market-clearing interest rates and the equilibrium quantity of lending are given by the intersection between the demand and supply curves (see [Figure 1.1](#)). At equilibrium, investment equals savings. An increase in interest rates augments the willingness of both savers and borrowers to defer current spending. Now consider the case of a positive shock on aggregate income. Assuming a constant ratio of consumption to income, savings increase and lead to a higher supply of loans for a given interest rate. The supply curve thereby shifts down to the right. Insofar as borrowers also have more income to finance current spending, the demand curve switches down to the left, which yields a new equilibrium interest rate. For each income level, there is a new equilibrium interest rate for which investment equals savings.

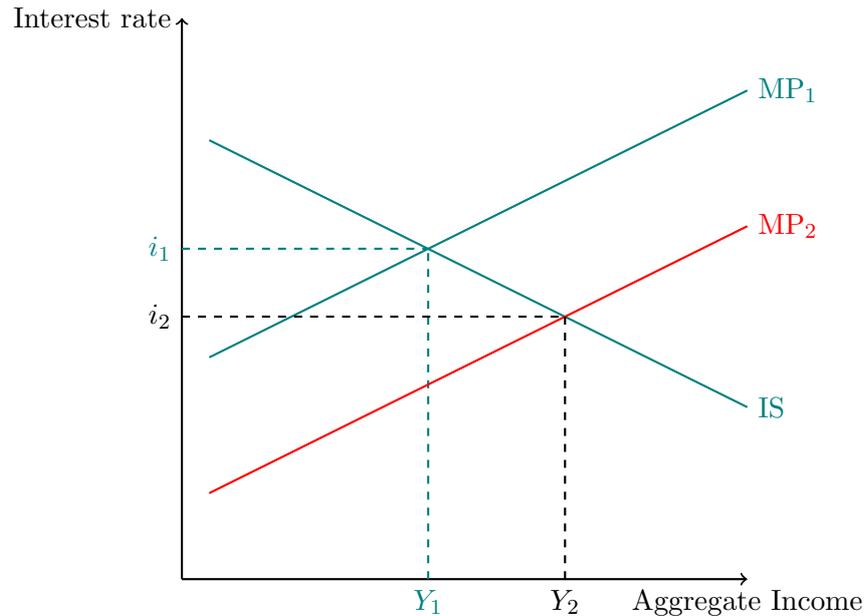


Figure 1.2: Effect of a Loosening of Monetary Policy on Interest Rates and Output

Alternatively, because income and the interest rate are jointly determined, for each possible level of the interest rate, there is a corresponding level of income for which the supply and demand for funds are equal. Plotting the equilibrium interest rate for any level of aggregate income, that is the locus of equilibria in the LS/LD model, yields the Investment-Saving (IS) curve. The downward sloping IS curve describes the sensibility of investment, or equivalently output, to the interest rate. The demand for capital is negatively correlated with the cost of funds, holding constant investment opportunities. When new investment opportunities arise, the demand curve shifts to the right, increasing the desired capital stock for a given interest rate. An increase in the market interest rate therefore reduces the desired capital stock, all else being equal. If interest rates were freely determined, at equilibrium the interest rate would be equal to the expected marginal profitability of capital adjusted for risk, meaning that the supply curve would be horizontal. In practice however, the central bank adjusts the policy rate according to the level of economic activity (relative to potential), which yields the upward sloping monetary policy (MP) curve. The IS/MP framework³ describes the joint determination of the equilibrium level of output and the interest rate (see Figure 1.2).

The Aggregate Demand (AD) (see Figure 1.3) represents the locus of equilibria in the IS–MP model, that is the set of IS–MP equilibrium incomes at different potential price levels. The higher the inflation, the lower the level of output demanded. Finally, the Phillips curve Aggregate Supply (AS) curve describes the relationship between inflation and output, i.e. the level of output supplied by firms as a function of the prices level. The intersection between the AS and the AD curve yields the equilibrium level of prices and output. Assuming price

³The IS/MP offers an alternative modeling of the money market than the IS/LM model. While central bank controls money supply in the IS/LM model, the IS/MP model instead assumes that it manages the interest rate according to a Taylor rule and let the supply of money be determined from that, in line with modern central banking practice.

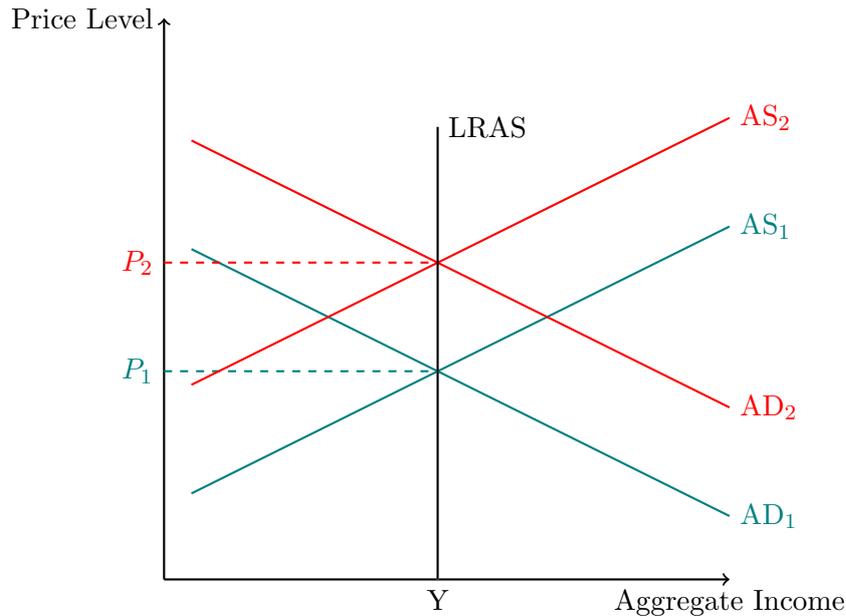


Figure 1.3: Impact of a positive demand shock

rigidities, a positive demand shock shifts the AD curve to the right and moves the equilibrium along the initial AS curve, which is temporarily left unchanged. Real GDP increases and the price level rises. In the long-run, wages adjust upward to reflect higher prices and the AS curve shifts leftward so that the economy returns to its long-run equilibrium (potential GDP), with inflation permanently higher. The Long-Run Aggregate Supply (LRAS) curve is thereby vertical.

This simple model illustrates the joint determination of interest rates and real outcomes. The relationship between interest rates and investment, the so-called user-cost of capital channel of Keynes [1936], can be easily micro-founded. Firms undertake new investment until the marginal rate of return of an investment equals the opportunity cost of capital. When allowing for nominal rigidities, it is the ex-ante real interest rate that matters rather than the nominal one. The New Keynesian IS curve illustrates that output is driven by expectations of future output as well as the ex-ante real interest rate:

$$y_t = \alpha_1 y_{t-1} + \alpha_2 E_t y_{t+1} + \beta (R_t - E_t \pi_{t+1} - \bar{r})$$

where y is output in deviation from steady state, R is a short-term nominal interest rate, π is the inflation rate and \bar{r} is the equilibrium natural real interest rate. An unexpected increase in the policy rate leads to an increase in the ex-ante real interest rate, which in turn reduces consumption and investment spending. Price stickiness allows nominal shocks to have real effects and imply the existence of a New Keynesian Phillips curve. Even when nominal interest rates are at the zero-lower bound, a commitment by the central bank to future expansionary monetary policy can lower long-term interest rates and raise expected inflation, thereby driving down real interest rates and stimulating spending (Eggertsson and Woodford [2003]). This is one of the reasons why the “management of expectations” has

become a major tool for the conduct of monetary policy (Woodford [2003]).

The interest rate also affects consumption via the Intertemporal Substitution channel, whereby current consumption depends negatively on interest rates. For instance, in the simple case where the utility function is defined over current and future consumption:

$$U(c_t, c_{t+1}) = u(c_t) + \beta E_t [u(c_{t+1})]$$

where the utility function $u(\cdot)$ is increasing and concave, reflecting a desire for more consumption but a declining marginal value of additional consumption. The curvature of the utility function generates risk-aversion and a preference for consumption streams that are steady over time and across states. $\beta < 1$, illustrates the fact that the household puts less weight on future utility than current utility. Impatient households require a higher interest rate to convince them to save for future consumption. The household receives an exogenous stream of income y_t and y_{t+1} in the two periods and decides whether to save or borrow an amount s_t in the first period via a financial contract at an interest rate r_t . The household faces two budget constraints in t and $t + 1$:

$$c_t + s_t = y_t$$

$$c_{t+1} = y_{t+1} + (1 + r_t)s_t$$

The maximization of $U(c_t, c_{t+1})$ over c_t and c_{t+1} yields the Euler equation that links the marginal rate of substitution between current and future consumption with the real interest rate:

$$u'(c_t) = \beta(1 + r_t)u'(c_{t+1})$$

The Euler equation states that at equilibrium, the marginal utility from consuming more today must be equal to the marginal utility of saving more today. If the household were not indifferent between consuming and saving more, he could indeed increase utility by doing one or the other.

Consumption-based Asset Pricing Models (CAPM) generalize the Euler equation to all financial assets and offer an insightful framework to study the joint determination of consumption and asset prices. Assuming that the consumer can buy a financial asset at price p_t that yields at time $t + 1$ a payoff (price + dividend) of:

$$x_{t+1} = p_{t+1} + d_{t+1}$$

Maximizing over consumption yields:

$$p_t = E_t \left[\beta \frac{u'(c_{t+1})}{u'(c_t)} x_{t+1} \right]$$

$p_t u'(c_t)$ is the loss in utility if the investor buys another unit of the asset. $E_t[\beta u'(c_{t+1}) x_{t+1}]$ is the increase in expected discounted utility from the payoff at $t + 1$. At equilibrium, the consumer buys or sells the asset until the marginal utility of today's consumption is equal to what an extra unit of the asset would yield in utility next period. The quantity $m_{t+1} =$

$\beta u'(c_{t+1})/u'(c_t)$ is called the stochastic discount factor or pricing kernel⁴. In addition, we know that:

$$\text{Cov}(m_{t+1}, x_{t+1}) = E(m_{t+1}x_{t+1}) - E(m_{t+1})E(x_{t+1}) \Rightarrow p_t = E(x_{t+1})E(m_{t+1}) + \text{Cov}(m_{t+1}, x_{t+1})$$

The price of an asset therefore increases if its payoff is negatively correlated with consumption, because it makes consumption less volatile. When the financial asset is the risk-free rate, the pricing equation becomes:

$$R_t^f = \frac{1}{E(m_{t+1})}$$

Getting rid of uncertainty and using a constant relative risk aversion utility function $u(c) = c^{1-\gamma}/(1-\gamma)$:

$$R_t^f = \frac{1}{\beta} \left(\frac{c_{t+1}}{c_t} \right)^\gamma$$

This simple framework illustrates that interest rates are all the more sensitive to consumption growth than the curvature of the utility function (γ), which reflects risk-aversion⁵, is high, or equivalently than the elasticity of intertemporal substitution ($1/\gamma$) is low. The higher risk-aversion, the stronger the individual is willing to smooth consumption over time despite changes in interest rate incentives. By the same token, higher consumption volatility increases the willingness to save, which drives down interest rates.

Asset pricing models provide insightful guidance about the joint determination of consumption and asset prices. These stylized models, however, are unable to replicate key empirical stylized facts on asset prices, such as the equity premium puzzle (Mehra and Prescott [1985]) or the excess volatility of asset prices (Shiller [1981]). One way to account for these mechanisms is to introduce frictions that generate time-varying risk aversion, which links investors' risk aversion to macroeconomic volatility. These frictions may arise in the context of habit formation (Campbell and Cochrane [1999]), Epstein-Zin preferences (Epstein and Zin [1989]), rare disasters (Barro [2006], Gabaix [2012]) or heterogeneous agents (Constantinides and Duffie [1996]).

An additional transmission mechanism, closely related to the user-cost of capital (Hayashi [1982]), manifests through the Tobin's Q theory of investment (Tobin [1969]). Based on the empirical observation that corporate investment and the stock market are positively correlated across time series and in the cross-section, this channel states that changes in stock prices influence the investment decision of the firm. Consider, for example, the investment decision

⁴The existence of a positive stochastic discount factor is guaranteed by the absence of arbitrage in markets without transaction costs. Market completeness ensures that the stochastic discount factor is unique.

⁵Risk aversion describes the consumer's reluctance to substitute consumption across states of the world (meaningful even in an atemporal setting), whereas the elasticity of intertemporal substitution describes the consumer's willingness to substitute consumption over time (meaningful even in a deterministic setting).

⁶The fact that the elasticity of substitution is the reciprocal of the coefficient of relative risk aversion can be relaxed by using Epstein-Zin preferences instead of the power utility.

of firm with constant return to scale and a Cobb-Douglas production function:

$$V = \max_{I_t, k_{t+1}} E_0 \sum_{t=0}^{\infty} \frac{1}{1+r} \left[a_t f(k_t, l_t) - w_t l_t - I_t - \Phi\left(\frac{I_t}{k_t}\right) \right] \quad \text{such that} \quad k_{t+1} = I_t + (1-\delta)k_t$$

where r , k , l and I are the real interest rate used to discount profit, capital, labor and productivity respectively. $\Phi(\cdot)$ is an increasing and convex adjustment cost. Absent adjustment cost, the equilibrium level of investment would be fully determined by saving supply. The first order condition relative to I_t yields:

$$Q_t = 1 + \phi'\left(\frac{I_t}{k_t}\right)$$

where Q_t , the so-called Tobin's Q, is the Lagrange multiplier in front of the law of motion of capital. It is the ratio of the market value of a firm's capital over the replacement cost of capital and measures how much firm value increases once the constraint is relaxed. Having the constraint relaxed means having one more unit of installed capital, or one more unit of k_{t+1} . Since the level of k_{t+1} is already optimized, the firm will reduce current investment by one. By investing one unit less of capital today, the firm increases current profit by the same amount and reduces adjustment costs by $\Phi'\left(\frac{I_t}{k_t}\right)$, which also raises current profits. It follows that $Q_t = \partial V / \partial k_{t+1}$. Using a quadratic adjustment cost such as $\Phi\left(\frac{I_t}{k_t}\right) = \frac{\phi}{2}\left(\frac{I_t}{k_t} - \delta\right)^2$:

$$Q_t = 1 + \phi\left(\frac{I_t}{k_t} - \delta\right) \Leftrightarrow \frac{I_t}{k_t} = \frac{1}{\phi}(Q_t - 1) + \delta \Leftrightarrow I_t \geq 0 \Leftrightarrow Q_t \geq 1$$

Investment as a fraction of the size of the firm (its capital stock) only depends on Q_t . Tobin's Q therefore establishes a natural link between asset prices and corporate investment. If the market value of the physical capital of a firm exceeds its replacement cost, then capital book value ("in the firm") is higher than its market value ("outside the firm") and the cost associated with raising external financing is low. Value can thus be added by investing until Q converges to its equilibrium level of one. For residential investment, for instance, this means that construction becomes profitable when property prices rise above construction costs. In practice, however, we only observe the average value of capital inside the firm (stock market value) relative to capital outside the firm (net worth), rather than the marginal value of capital ($\partial V / \partial I$). The two are equal in the case of perfect competition and constant returns to scale as the value of the firm changes linearly with k (Hayashi [1982]), which allows to test the validity of the Tobin's Q mechanism empirically. If the theory works, Q_t should be a sufficient explanatory variable for investment. However, empirical tests of this hypothesis show that the regression leaves large unexplained residuals that are correlated with fundamentals and cash-flows (Blanchard et al. [1993]). One reason for this could be that the assumptions of perfect competition, constant return to scale or convexity of adjustment costs may not hold empirically. Philippon [2009] instead uses corporate bond prices to fit investment U.S. data, on the premise that equity incorporate factors that are unrelated to the investment profile of the firm, such as changes in attitudes towards risk, and because equity investors tend to have a preference for positive skewness (Brunnermeier et al. [2007]).

An additional channel of transmission from asset prices to the real economy is the wealth effect channel. This channel is based on the permanent income models of consumption of [Ando and Modigliani \[1963\]](#) and [Friedman \[1957\]](#), which state that consumption depends on lifetime resources, including financial wealth. Changes in asset prices deemed permanent and consistent with long-run fundamentals should therefore affect consumption. Albeit intuitive from a theoretical point of view, there is little empirical evidence supporting this channel. Estimates of the propensity to consume out of financial wealth have been found to be relatively unstable. [Catte et al. \[2004\]](#), in a study of OECD countries, find that the long run marginal propensity to consume out of financial wealth is about 0.035% for the OECD average. Housing wealth has been found to have a larger effect on consumption than equity wealth ([Carroll et al. \[2011\]](#)). This could result from the fact that because equity prices are more volatile than property prices, changes in equity prices are less likely to be perceived as permanent ([Cecchetti \[2008\]](#)).

The model of [Blanchard et al. \[1981\]](#) encompasses all the neoclassical channels of transmission outlined herein and extends the IS-LM model to other asset classes than the sole short-term interest rate. The model emphasizes the joint response of output, money, the stock market and the yield curve to policy changes. As in the standard IS-LM model, output is determined by aggregate demand/spending. Aggregate demand (D_t) is driven by current income (y_t) and the value of the stock market (Q_t), via the impact of wealth effects on consumption and the Tobin's Q theory of investment:

$$D_t = \alpha.Q_t + \beta.y_t \quad \text{with} \quad \alpha > 0 \text{ and } \beta > 0$$

Via its link with stock prices, aggregate spending is a positive function of future expected output and a negative function of current and future interest rates.

Output growth is related to current output and spending⁶:

$$\Delta y_t = \sigma(D_t - y_t) = \sigma(\alpha.Q_t - b.y_t) \quad \text{with} \quad \sigma > 0 \text{ and } b = 1 - \beta$$

The model is closed by characterizing equilibrium in the money market and the arbitrage relationship between short and long-term interest rates. The demand for real money balances (M_t/p_t) depends positively on current output via transaction purposes and negatively on the interest rate i_t and inflation π_t which increase the opportunity cost of holding money:

$$\frac{M_t}{p_t} = \gamma.y_t - \kappa.i_t - \theta.\pi_t \quad \text{with} \quad \gamma > 0, \kappa > 0 \text{ and } \theta > 0$$

Finally, the Expectations hypothesis ensures that the long-term interest rates ($i_{t,t+h}$) is equal to the average of one-period yields over the same period ($i_{t,t+1}, i_{t+1,t+2}, \dots, i_{t+h-1,t+h}$):

⁶Insofar as output growth is stationary while output and the stock market value are I(1), this is an error correction equation which states that the stock market and the real economy cannot diverge substantially.

$$(1 + i_{t,t+h})^h = \prod_{k=0}^{h-1} (1 + i_{t+k,t+k+1}) \Rightarrow i_{t,t+h} \approx \frac{1}{h} \sum_{k=0}^{h-1} i_{t+k,t+k+1}$$

These strong theoretical underpinnings notwithstanding, the quantitative impact of neo-classical channels of transmission of financial factors to the real economy has been found to be very limited. As suggested by [Bernanke and Gertler \[1995\]](#), “*empirical studies of supposedly “interest-sensitive” components of aggregate spending [fixed investment, housing, inventories and consumer durables] have in fact had great difficulty in identifying a quantitatively important effect of the neoclassical cost-of-capital variable*”. These limitations suggest to relax the assumption of frictionless financial markets to allow for stronger transmission mechanisms.

1.2.2 Financial frictions

When financial frictions arise, the allocation of financial resources is no longer optimal, either because borrowers are constrained in their capacity to raise new funds, or because the financial sector supplies too little or too much credit relative to the demand for funds. It is no longer the case that any investment with a positive net return will be undertaken. As we will see, a major implication of financial frictions is that the cost of external funding, i.e. the market cost of capital, is higher than the return on capital earned by savers. As a result, internal and external resources are no longer perfect substitutes. Moreover, the distribution of wealth now matters, as agents’ net worth affects the cost of external funding.

Demand-side frictions

In the absence of information asymmetry, there is no active role for financial intermediaries to channel funds from savers to borrowers. As a result, the bond market, where funds flow directly from borrowers to savers, and the loan market, are perfect substitutes. Empirical evidence however suggests instead that loans and bonds are different things. One example supporting this is the low correlation between the timing of corporate default and banking crises ([Giesecke et al. \[2014\]](#)). Additionally, [Adrian et al. \[2013b\]](#) show that the issuance of bonds compensates the drop in bank lending, even when financial conditions tightened in both markets. The fact that loans and bonds are not perfect substitute suggests an active role for the banking sector.

The Bank Lending channel ([Bernanke et al. \[1993\]](#); [Bernanke and Gertler \[1995\]](#)) arises from the special role played by banks regarding maturity transformation and liquidity provision for bank-dependent agents that are unable to substitute with other forms of external financing. Banks have the power to mitigate asymmetric information about the quality or riskiness of the borrowers’ investment projects, as well as incentive problems that generates adverse selection and moral hazard in capital markets. The monitoring skills of banks help the investor to distinguish between bad luck and the diversion of funds. These information

asymmetries lead to transaction costs and incomplete financial markets in the sense that not every worthwhile project is financed. [Bernanke \[1983\]](#) argues that the Bank Lending channel played a crucial role during the Great Depression. The fall in credit quantities was not the passive response of a depressed demand for loans owing to deteriorating economic conditions.

In order to overcome the asymmetric information problem, bank-dependent firms and households must post collateral ([Stiglitz and Weiss \[1981\]](#)) or maintain some stake in the project. Fundamentally, a financially strong borrower has more “skin in the game,” and consequently has greater incentives to make well-informed investment choices. When the borrower’s net worth is low relative to the amount borrowed, the borrower has a greater incentive to default on the loan. As a result, holding constant investment opportunities, the internal resources of a firm influence the cost of external funds. The information cost is transmitted to the borrowers via a spread above the interest rate received by savers, which creates a wedge between the cost of external financing and internal funding. In the model of [Holmstrom and Tirole \[1997\]](#), credit can flow either directly from savers to borrowers or indirectly via the banking sector. Firms follow a pecking order of financing choices. Firms with low net worth only have access to banks, while firms with high net worth also have access to the bond market, which is typically cheaper. Macroeconomic models with asymmetric information help to explain part of the volatility of investment unexplained by expected future profitability or the user cost of capital in neoclassical models. Procyclical changes in economic agents’ net worth over the Business Cycle exaggerate swings in investment, spending and production. This amplification mechanism is known in the literature as the “Financial Accelerator” and arises either because the wedge between external and internal finance moves countercyclically ([Bernanke and Gertler \[1995\]](#)), or because of procyclical changes in the value of collateralizable assets ([Kiyotaki and Moore \[1997\]](#)). With the Financial Accelerator, a temporary adverse shock can be very persistent as it takes a long time for firms and households to rebuild their net worth through retained earnings or savings.

Two types of microfoundations have been used to model the Financial Accelerator mechanism. In the “costly state verification” ([Townsend \[1979\]](#)), the friction arises because the lender does not observe the outcome of the project undertaken with the funds. The true payoff can only be known with certainty by paying a monitoring cost that is passed to the borrower in the form of higher interest rates, proportionally to the amount borrowed. The quantity of borrowing is not restricted *per se*, but additional borrowing becomes unattractive at some point because of the subsequent increase in the price of credit. The costly state verification has been used in the first stream of general equilibrium models with Financial Accelerator mechanisms ([Carlstrom and Fuerst \[1997\]](#); [Bernanke et al. \[1999\]](#)). In [Bernanke et al. \[1999\]](#), the borrowing capacity of firms depends negatively on the External Finance Premium, which is defined as the difference between the cost of raising funds externally and the opportunity cost of internal cash flows. The External Finance Premium that a borrower must pay depends inversely on the strength of the borrower’s financial position.

The “costly enforcement” setup ([Kiyotaki and Moore \[1997\]](#)) offers an alternative solution

to model demand-side financial frictions. Because in the event of default the lender can only recover a fraction of the debt, he imposes a collateral constraint, such that a borrower can only borrow up to a fraction of the value of his assets. While in the costly state verification setup, credit was rationed by prices, it is also rationed by quantities in the costly enforcement setup. Firms' ability to obtain loans depends directly on the value of the collateral they can offer. The level of credit rationing will be countercyclical owing to the procyclical value of collateralised assets and credit acts as an amplifier of the Business Cycle.

Along this line, [Gerali et al. \[2010\]](#) augment the model of [Smets and Wouters \[2007\]](#) with a collateral-based Financial Accelerator. The economy is populated by patient and impatient households that work and accumulate housing and by entrepreneurs that produce consumer goods. Impatient households and entrepreneurs can borrow money subject to a collateral constraint. The heterogeneity in agents' discount factors makes external financing more attractive than internal funds and ensures that the borrowing constraint is always binding, thereby generating positive financial flows in equilibrium ([Iacoviello \[2005\]](#)). The impatient households' borrowing constraint is:

$$(1 + r_t^b)b_t \leq m_t E_t[q_{t+1}\pi_{t+1}]h_t$$

where r^b is the interest rate on borrowings, b the amount of credit borrowed by the impatient households, q is the price of housing, h is the amount of housing owned by the impatient household, π is the inflation rate and m is the loan-to-value ratios, which captures fluctuations in credit availability. The borrowing constraint entails that the expected value of their housing stock must ensure payment of debt and interests. The optimal borrowing choice of the impatient household depends on the expected real cost of additional borrowings and on the Lagrange multiplier associated with the collateral constraint, which represents the increase in lifetime utility resulting from borrowing an extra unit of loan and reducing consumption next period. Fluctuations in housing prices affect the borrowing capacity of impatient agents and firms and generate large swings in economic activity. In practice however, the jury is still out on the empirical relevance of the collateral approach. For instance, [Azariadis \[2018\]](#) finds that unsecured debt is procyclical contrary to secured debt, which is more or less acyclical, while the opposite should prevail based on the collateral approach.

Undertaking an assessment of the quantitative relevance of the Financial Accelerator mechanism is challenging as it requires to control for changes in investment opportunities when testing the correlation between changes in net worth or internal funds and spending, as firms with profitable investment opportunities may also enjoy stronger cash flows ([Fazzari et al. \[1988\]](#)). The housing market is a good laboratory to pin down the dynamics of the Financial Accelerator because shocks to real estate worth affect the borrowing capacity without being correlated with household or corporate spending. Moreover, housing wealth accounts for half of household wealth in most developed economies and tends to move together with aggregate consumption expenditures. Residential real estate constitutes a major source of collateral not only for households but also for small firms ([Adelino et al. \[2015\]](#)). [Almeida et al. \[2006\]](#) show evidence of a collateral-based Financial Accelerator in interna-

tional housing markets by exploring cross-sectional differences in the spending responses of financially-constrained agents to aggregate income shocks. On the corporate side, [Catherine et al. \[2017\]](#) investigate the aggregate effects of collateral financial frictions based on the relationship between real estate worth and corporate investment. Their findings suggest that in the U.S., financing constraints reduce welfare by 9.4% and output by 11%. Most of the output loss bears upon a lower capital stock rather than subdued productivity due to misallocation. In Japan, [Fuchi et al. \[2005\]](#) study the effect of the bursting of the real estate bubble in 1989 and estimate that a negative shock of 10% to the net worth of companies entailed a long-lasting 40% reduction in capital expenditures.

[Stein \[1996\]](#) adds an additional departure from perfect financial market by allowing stock prices to have a non-rational component δ relative to the efficient-market value (the present value of future cash flows). The firm can invest K in the first period, which yields a gross return of $f(K)$ in the next period, where $f(\cdot)$ is an increasing and concave function. The net present value of this investment is $f(K)/(1+r) - K$, where r is the discount rate. The optimal level of investment in the absence of financial frictions K^* is therefore $f'(K^*) = 1+r$. The firm can issue equity e subject to $0 \leq e \leq e^{\max}$. Financing and investment are linked by a leverage constraint:

$$e + W - K(1 - \bar{D}) \geq 0$$

where W is the firm's pre-existing wealth and \bar{D} is the fractional debt capacity of the new assets. This constraint implies that the firm's debt ratio can fall below \bar{D} but cannot exceed it. The firm's optimization problem is:

$$\max_{e, K} \frac{f(K)}{1+r} - K + \delta e$$

subject to

$$e + W - K(1 - \bar{D}) \geq 0, \text{ and } 0 \leq e \leq e^{\max}$$

When the stock is overvalued relative to fundamentals ($\delta > 0$), the firm invests at its best level K^* and issues as much equity as possible $e = e^{\max}$. Because the leverage constraint is one-sided, investment will only be sensitive to equity prices when the stock is undervalued ($\delta < 0$). Two cases arise:

1. if the firm has sufficient wealth ($W - K^*(1 - \bar{D}) \leq 0$), it will invest at its best level K^* with its own wealth ($e = 0$);
2. if the firm does not have sufficient wealth ($W - K^*(1 - \bar{D}) < 0$), it will under invest ($K < K^*$) and the level of equity issuance will depend on the level of investment \bar{K} defined such that $f'(\bar{K})/(1+r) = 1 - \delta(1 - \bar{D})$:
 - (a) if $W - \bar{K}(1 - \bar{D}) < 0$, $K = \bar{K}$ and $e = \bar{K}(1 - \bar{D}) - W > 0$, i.e. the firm issues equity based on the degree of undervaluation and its debt capacity;
 - (b) if $W - \bar{K}(1 - \bar{D}) \geq 0$, the firm does not issue equity ($e = 0$) and invests as much as it can subject to its wealth W and the leverage constraint, such that $K = W/(1 - \bar{D})$.

The key takeaway from this model is that a firm with no debt and a stockpile of cash can insulate its investment decisions from irrational movements in its stock price. On the contrary, for “equity-dependent” firms with low net worth and whose stock price is undervalued, the non-fundamental component of stock prices will be a key driver of investment, as the firm would have to issue undervalued equity to invest at its first-best level. Investment tends towards its first-best level with increasing net worth. Baker et al. [2003] show empirically that undervaluation acts like a financial constraint that discourages investment for “equity-dependent” firms for which $W \leq K^*(1 - \bar{D})$.

Supply-side financial frictions

Although demand-side financial frictions help to understand the qualitative importance of financial factors as an amplifier of economic disturbances, recent financial events suggest that they do not give the full picture of financial macro-linkages. In particular, the two workhorse models of demand-side financial frictions used in macroeconomics (Benanke and Gertler [1989]; Kiyotaki and Moore [1997]) do not generate enough asset price volatility for the Financial Accelerator mechanism to have a significant aggregate quantitative impact on the Business Cycle (Kocherlakota [2000]). As suggested by Adrian et al. [2013b], “*net worth, by itself, cannot serve as the state variable that fully determines financial conditions*”. In particular, these models exhibit the same qualitative response to economic disturbances, albeit amplified, than the standard IS-MP model. This does not mean that demand-side frictions are not relevant, but that part of the story is missing. For instance, an implicit assumption of models featuring collateral financial constraints is that borrowers always honor their debts. In models with costly state verification, the External Finance Premium required ex-ante by banks technically insulates banks from solvency problems related to borrower default. In real life, borrower default entails a reduction of financial intermediaries’ net worth which undermines their capacity to meet credit demand unless they raise new capital. The introduction of financial frictions on the supply-side of credit provides a powerful role to the financial sector and allows for fluctuations in credit supply and economic activity that are unrelated to changes in the demand for funds or the credit quality of borrowers.

The first type of supply-side friction arises by relaxing the assumption that banks can costlessly transform savings into loans via a constant returns to scale technology. In that case, it is possible that the banking sector is unable, or unwilling, to meet credit demand. To this end, Woodford and Curdia [2008] and Gerali et al. [2010] introduce a loan production function with diminishing return, meaning that the cost of originating and managing loans increases with the volume of lending. This gives rise to a second spread, in addition to the External Finance Premium, that corresponds to the marginal cost of lending for financial intermediaries and which increases with the volume of lending.

A second source of distortion in the provision of funds relative to economic fundamentals bears upon leverage and borrowing constraints on financial intermediaries. These constraints

typically arise from regulatory capital requirements (Gerali et al. [2010]), or from banks' creditors, in order to limit the loss incurred in bad states of the world. This creates a link between financial intermediary's capital or net worth and their capacity to raise funds for lending purpose. This channel of transmission is known as the Bank Capital channel for the banking sector but applies more generally to all lending financial institutions via the so-called Leverage channel. This channel is akin to a Financial Accelerator mechanism for financial intermediaries. The rationale of this mechanism is threefold. First, better capitalized banks can more easily absorb losses on their loan and asset portfolios. Second, like any firm, financial intermediaries may face borrowing constraints that makes net worth a relevant state variable for their funding capacity. For instance, in the 1990s, the decline in the Japanese stock market led to a reduction in the U.S. lending-market share of Japanese banks, especially for banks with weaker balance sheets (Peek and Rosengren [1997]). Third, financial net worth and leverage may also be linked by the reliance of financial institutions on collateralized short-term borrowing to finance their asset positions and lending. Haircuts and margins, which dictate the share of financing for a unit of collateral, tend to be highly procyclical, thereby amplifying the natural procyclicality of lending. As illustrated by Geanakoplos [2010] and Gorton and Metrick [2012], an increase in collateral requirements can significantly undermine the risk-bearing capacity of the financial system and limit the leverage of the financial sector. In the model of Gertler and Kiyotaki [2010] depositors face the risk of bank default and thereby require some insurance in the form of sufficient net worth, which creates a link between banks' net worth and their leverage ratio. In addition to demand-side financial frictions, Gerali et al. [2010] augment the standard New-Keynesian model with two financial frictions on the credit supply-side. First, they introduce monopolistic competition in the banking sector, where market power is modeled in the spirit of Dixit and Stiglitz [1977]. Banks can now charge a time-varying mark-up over the marginal cost of loan production and deposits origination. Second, Gerali et al. [2010] impose an exogenous target for banks' leverage, which links financial intermediaries balance sheet position with lending. Banks manage lending spreads so as to keep their leverage ratio in line with the target. Because capital is accumulated out of retained earnings, the leverage ratio varies with economic conditions. This creates a positively-sloped loan-supply curve that shifts procyclically with changes in the policy rate and banks' profitability, and affects the equilibrium level of credit provision.

The Risk-taking channel is an additional channel that entails endogenous fluctuations in the supply of credit (Borio and Zhu [2011]; Adrian and Shin [2010a]). This channel, which is close to the Leverage channel, describes how changes in the perception and attitude towards risk drive the leverage choice of financial intermediaries (Adrian and Shin [2006]; Adrian et al. [2013b]). For instance, during "hot markets" periods, portfolio choices are largely driven by greater investor optimism (Helwege and Liang [2004]). Adrian and Shin [2008b] set forth this channel and show that financial institutions manage their portfolio risk according to a Value-at-risk (VaR) constraint⁷. A fall in measured risk translates directly into an increase in bank leverage, which adds more procyclicality to lending. As a result, while leverage should

⁷The Value-at-Risk is a quantile measure on the loss distribution defined as the maximum possible loss whose probability is at most α . Keeping the VaR lower than equity capital ensures to remain solvent with probability higher than $1 - \alpha$.

drop when asset prices boost net worth and be countercyclical, it is in fact highly procyclical (Adrian and Shin [2008a]). Additionally, when interest rates and risk premia on traditional asset classes are low relative to historical levels, or in the case of nominal return targets, financial institutions are tempted to turn to riskier investment strategies in order to generate sufficient return to meet their commitments (Rajan [2006]).

Liquidity frictions may also distort the allocation of financial resources relative to its optimal level. Liquidity can take two forms (Brunnermeier and Pedersen [2009]). Market liquidity is the degree to which a security can be bought or sold in the secondary market without modifying its price. Funding liquidity represents the ease of raising new funds. The two concepts are closely related. For instance, market liquidity on the secondary market is of the utmost importance for the funding liquidity of agents willing to issue debt or equity. By the same token, market liquidity is a crucial component of short-term collateralized lending markets, where investment requires to raise new funds, either through the sale of existing assets, or by using another financial asset as collateral for borrowing funds. Liquidity conditions can be a source of disruption when market liquidity on the asset side of the balance sheet and funding liquidity on the liability side of the balance sheet interact in the form of a liquidity spiral. In periods of heightened financial stress, the demand for safe liquid assets may increase and lead to flight to quality and liquidity portfolio movements, aggravating liquidity conditions on risky assets. Moreover, the ex-post implications of an adverse liquidity shock affect the ex-ante demand for liquid assets. In anticipation of potential adverse non-insurable idiosyncratic shocks, market participants have the desire to hold liquid assets and to preserve a “liquidity buffer”, which may affect their lending choice and lead to inefficient aggregate outcome.

1.3 The ambiguous effect of finance on the macroeconomy

1.3.1 Finance and growth

In Schumpeter’s theory (Schumpeter [1954]), where innovation and entrepreneurship are the driving forces of economic growth, finance spurs technological progress by reallocating investment funds to the most profitable ventures. By improving resource allocation, a well-functioning financial market increases the level of physical capital formation and therefore long-term growth. Finance may for instance support competition by shifting investment towards expanding innovative sectors. Second, strong institutions fostering investor protection and efficient bankruptcy laws limit the cost of firm exit. According to Schumpeter’s view, financial deepening, either in the form of broader participation or increasing provision of financial services, is therefore a growth-propelling engine.

In practice, the role of finance on growth is still a matter of debate, chiefly owing to potential omitted variables or reverse causality. For instance, financial development could increase in anticipation of future productivity growth. Seminal work by King and Levine [1993] provides tangible evidence of a strong and significant association, not necessarily causal, be-

tween economic growth and measures of financial development⁸. In an attempt to deal with the endogeneity issue, [La Porta et al. \[1997\]](#) use the legal origin of each country as an instrumental variable to extract the exogenous component of financial development, on the premise that an efficient legal system should better promote a contract-based activity such as finance. However, the legal system may affect economic growth otherwise than via financial development, thereby invalidating the exclusion restriction of the instrumental variable ([Rajan and Zingales \[2003\]](#)). With industry-level data, [Rajan and Zingales \[1998\]](#) confirm Schumpeter’s hypothesis by showing that industries that are more dependent on external financing grow faster in countries with more-developed financial markets. As regards the mechanism underlying the impact of finance on growth, empirical evidence suggests that financial development improves the allocation of resources, more than enhancing capital accumulation ([Levine \[2005\]](#)), and lowers the cost of external finance ([Fisman and Love \[2007\]](#)). [Bertrand et al. \[2007\]](#) show that the French banking reform of 1985 that allowed capital flows to be determined by market forces resulted in an improvement in allocative efficiency across firms and a higher rate of restructuring, in line with the “creative destruction” described by Schumpeter.

However, the recurrence of financial crises has shown that the benefits of finance are not an open-ended linear function of intensity and volume. First, not all kinds of financial deepening are positive for growth. [Beck et al. \[2012\]](#) find that financial deepening improves growth via enterprise credit more than household credit. While household credit has been shown to also stimulate entrepreneurship ([Adelino et al. \[2015\]](#)), mortgage lending instead tends to crowd out business credit. As documented by [Chakraborty et al. \[2017\]](#), in the two decades that preceded the GFC, mortgage lending increased dramatically relative to commercial lending in the U.S.

Second, the allocation of financial resources matters. In the theory of Wicksell ([Wicksell \[1907\]](#)), growth happens only when firms with a return on invested capital higher or equal to the natural rate have access to capital. When the market rate is below the natural interest rate⁹, undeserving investors without the necessary rate of return get access to capital and a large share of the available capital is wasted, potentially affecting the structural growth rate of the economy ([Hansen \[1939\]](#)). When the market interest rate is below the natural rate of interest, “zombie firms” emerge, i.e. firms that are structurally unable to cover debt servicing costs from current profits ([Caballero et al. \[2008a\]](#)). The survival of “zombie firms” weigh on aggregate productivity by impairing the creative destruction process ([Gopinath et al. \[2017\]](#)) and the exit of low productivity firms ([Dias et al. \[2016\]](#)). In addition, zombie firms crowd out funding for other firms and may dampen investment and labor supply for non-zombie firms ([McGowan et al. \[2017a\]](#)). [McGowan et al. \[2017b\]](#) and [Banerjee and Hofmann \[2018\]](#) document over the recent period a rise in the share of zombie firms and their probability of survival. The experience of Japan in the 1990s suggests that the costs to aggregate productivity from the inability to dispose of or restore to health such ailing firms are large ([Caballero et al. \[2008b\]](#), [Peek and Rosengren \[2005\]](#)). Financial deepening can also reduce

⁸Financial development is measured as the liquid liabilities of the financial system or credit to the private sector normalized, relative to GDP

⁹The natural interest rate is the interest rate that is compatible with a stable price level.

total factor productivity and become a drag on growth by benefiting disproportionately to low-productivity projects that require strong collateral (Cecchetti and Kharroubi [2015]), or by leading to an inefficient allocation of labor across sectors, as is typically the case with large credit expansions (Borio [2014]). Consider, for instance, the case of European periphery countries which experienced in the 2000s massive capital misallocation that materialized either in the form of a rapid growth in the non-tradable sector in Portugal (Reis [2013]), or through an increased dispersion in the return on capital across firms in Spain (Gopinath et al. [2017]). Moreover, as shown by Banerjee and Hofmann [2018] and Moll [2014], financial frictions tend to aggravate capital misallocation.

Third, finance may be subject to diminishing returns, whereby beyond a certain threshold, a further expansion in credit is associated with a less productive use of financial resources (Cecchetti and Kharroubi [2012]). Philippon and Reshef [2013] show that most of the rise in living standards from 1870 was obtained with less financial output and a smaller share of income spent on finance than what is observed after 1980. Acemoglu and Robinson [2013] argue that this increase in the share of finance could bear upon the fact that the financial sector did not necessarily deliver higher growth when the institutional foundations of prosperity were laid out by the middle of the 19th century, but that diminishing growth opportunities at some level of development make finance necessary to sustain growth.

Fourth, because finance is a commercial profit-seeking activity, agency issues may arise as financial institutions look for profitable opportunities that are not necessarily optimal from a welfare perspective, through an increase in financial fees or a cornering of highly skilled human capital.

Finally, as we shall see, financial liberalization involves a trade-off between growth and the likelihood of financial crises. While Rancière et al. [2006] find that the direct growth gain of financial liberalization outweighs the growth loss associated with more frequent financial crises, a vast literature instead points that the opposite prevails.

1.3.2 The Financial Cycle and Financial Crises

There are at least a couple of reasons why financial factors should be specifically studied. First, financial factors fluctuate autonomously, without necessarily being tied to the Business Cycle. Second, they tend to exhibit strong cyclicality and comovement. Therefore, they may affect economic activity significantly and increase its volatility. As we have seen earlier, it is possible that the financial sector supplies either too little or too much liquidity relative to economic fundamentals. The concept of “Financial Cycle” offers a convenient framework to study the fluctuations in credit and asset prices. It is defined by Borio [2014] as “*self-reinforcing interactions between perceptions of value and risk, attitudes toward risk and financing constraints, which translate into booms followed by busts*”. The upward phase of the Financial Cycle corresponds to credit increasing faster than nominal output and increasing asset prices.

In a neoclassical world, fluctuations in the Financial Cycle are tied to the Business Cycle, as they follow changes in the quantity of investment projects with a positive net present value. Departure from perfect financial markets instead induces fluctuations in the Financial Cycle that are potentially unrelated with the Business Cycle. In particular, fluctuations in the Financial Cycle occur at a lower frequency than those of the Business Cycle (Borio [2014]). The Financial Cycle waxes and wanes over time because of irrational changes in economic agents future income expectations, that are transferred into the present by the financial sector through credit creation and investment in financial securities (such as futures or options). Ensuing financial flows constitute a real-world counterpart to changes in expectations. These fluctuations are in turn amplified by the feedback loop between asset prices and leverage.

The global nature of the Financial Cycle and its spillovers can be a source of macroeconomic destabilization. As noted by Calvo et al. [1996], “*global factors affecting foreign investment tend to have an important cyclical component, which has given rise to repeated booms and busts in capital inflows*”. During credit booms, the cross-border component of credit tends to outpace domestic credit (Borio and Disyatat [2011]). Bayoumi and Swiston [2007] show that the main source of international spillovers is global financial conditions, while trade and commodities are less potent factors. This is consistent with Miranda-Agrippino and Rey [2015], which suggest that domestic financial conditions respond to global factors and may be inappropriate for some countries. Because of financial conditions spillovers from major financial centres, the “Mundell-Fleming trilemma”¹⁰ turns into a dilemma, in the sense that autonomous monetary policy is possible if and only if the capital account is managed, directly or indirectly via macroprudential policies (Rey [2015]). These spillovers increase the risk of unsafe funding patterns such as portfolio equity and debt portfolio debt, that are prone to sudden stops and potentially unrelated to domestic economic fundamentals.

Fluctuations of the Financial Cycle tend to fragilize the economy and sow the seeds of the subsequent economic contraction. For Eckstein and Sinai [1986], the Financial Cycle¹¹ arises from the interaction between balance sheet positions, liquidity and spending. It can be divided into four successive phases of accumulation, increasing instability, credit crunch and a final phase of rebuilding borrowers’ balance sheets and financial intermediaries’ liquidity. The accumulation stage is associated with the acquisition of physical and financial assets, initially backed by productivity gains on the real side. A key mechanism at this stage is the feedback loop between asset prices and leverage. Asset prices act both as wealth for the borrower and an insurance for the lender. Investors assume that asset prices will keep on going up and use leverage to maximize capital gains. The increase in leverage is concealed by the rise in asset prices. Lenders are all the more complacent that the value of borrowers’ collateral increases more quickly than the amount of lending, thereby mechanically decreasing loan-to-value ratios. Yield seeking investors turn to riskier asset classes, which depresses risk premia regardless of economic fundamentals. During this phase, the simultaneous shift in credit supply and demand implies that the equilibrium price of credit is left unchanged

¹⁰A country must choose between free capital mobility, exchange-rate management and monetary autonomy.

¹¹The authors use the term “flow of funds” or “credit cycle”.

despite the surge of leverage. Therefore, there is no restoring forces to keep credit expansion at bay. At some point however, the demand for funds outpaces the ability of the financial system to provide sufficient funding at affordable conditions. The liquidity squeeze rises the cost of external funding and deteriorates the balance sheet positions of the private sector, without completely discouraging spending. At that point, the economy is in a situation of financial instability, characterized by a mismeasurement of financial risk (Borio and Lowe [2002]) and a high vulnerability to shocks. The peak of the Financial Cycle often coincides with financial crises (Borio [2014]). The crunch is defined by Eckstein and Sinai [1986] as the “*collision of an expanding economy with a financial system that has been depleted of liquidity*”. It is characterized by a sharp increase in risky interest rates, reflecting the scramble for funds, rising delinquencies and defaults, and flight-to-quality portfolio rebalancing. At that moment, agents realize that expectations upon which spending plans are based are deceptive. As a result, external financing becomes more expensive when it is the most needed. Heightened cost-based inflation can be a confounding factor, as it increases the gap between spending and internal funds for both households and businesses.

Minsky [1980] gives an insightful narrative to explain the shift from a robust and safe to a fragile and crisis-prone financial system. He argues that the upward phase of the Financial Cycle bears upon the uncertainty that goes along any asset valuation process. Bouts of optimism entail that asset prices may depart significantly from the level suggested by economic fundamentals. Minsky [1980] identifies three stages of finance, from the most robust to the most fragile: 1) hedge finance, in which borrowers can meet all debt payments (interest and principle) from their cash flows; 2) speculative finance, in which borrowers can meet their interest payments but need to “roll over” their liabilities; and 3) Ponzi finance, whereby borrowers can neither repay the interest nor the original debt from the original investment and rely entirely on rising asset prices to refinance their debt. All of a sudden, lenders realize that financial assets are overpriced and borrowing constraints start to bind, forcing speculative and Ponzi units to sell some of their assets to meet their commitments. The financial crisis corresponds to a sudden unanticipated shift from a reasonably healthy equilibrium in terms of liquidity, risk-premia and volatility, to a state of financial stress. In the model of Eggerdsson and Krugman [2012], the equilibrium shifts to a financial stress regime when lenders become suddenly concerned about borrowers’ leverage, forcing them to deleverage and to adjust spending accordingly. The key insight from Minsky [1982] is the Financial Instability Hypothesis, whereby low volatility encourages more risk-taking and therefore “*stability is destabilizing*”. The key feature here is that the Financial Cycle downturn is purely endogenous, in the sense that there is no need for an external shock to switch from a good state of the world to a bad state of the world. In the model of Brunnermeier and Sannikov [2014], low volatility contributes to the buildup of endogenous risk by relaxing balance sheet constraints and inducing borrowers to increase leverage. High leverage however means that even a small adverse shock can have large consequences.

Purely economic recessions arise when corporate margins start to decline. Firms become worried about future aggregate demand and adjust investment and labor consequently. The

multiplier effects on current aggregate demand propagate throughout the economy and lead to a recession. The recession is typically short-lived as public spending or monetary policy can temporarily support demand. When the disruption originates in the financial sector, however, the consequences can be much more serious and long-lasting. In the classical balance-sheet recession, the private sector is left with declining wealth and high levels of debt, while financial institutions are not willing, or not capable of lending. Fisher [1933] provides an in-depth analysis of a balance-sheet recession, also known as the debt-deflation mechanism. Debt liquidation leads to a contraction of deposit currency, as bank loans are paid off, and to a slowing down of the velocity of circulation of money. This aggravates the downward pressure on prices, which in turn weigh on corporate profits, investment, trade and employment. The subsequent loss of confidence slows the velocity of money even further. Despite falling nominal interest rates, the real interest rate surges as a result of the drop in prices, which increases the burden of nominal debt¹². The economy is stuck in a vicious cycle of falling output and prices. The uncoordinated process of individual deleveraging rises the desire to save relative to invest. Banks are unable or unwilling to lend given the increase in default rates. The economy is left with highly leveraged balance sheets, depressed demand and adverse financial conditions, which may not only affect the cyclical component of output but also potential growth. Because interest rate cannot be negative, employment and aggregate output have to adjust for the lending market to clear, thereby depressing demand even more. Gerali et al. [2010] replicate the debt-deflation mechanism à la Fisher [1933] by introducing nominal debt as in Iacoviello [2005]. In the model, unexpected changes in the price level redistribute wealth resources from lenders toward borrowers¹³.

Financial crises may also originate in the banking sector in the form of bank runs. By investing in long-term assets and issuing short-term debt claims, financial institutions expose themselves to a liquidity mismatch. Bernanke [1983] argues that the credit crunch of the Great Depression, was related to banks struggling to keep their balance sheet as liquid as possible to avoid bank runs. In the model of Diamond and Dybvig [1983], banks must use long-term (relative to short-term consumption needs) collateral to back demand deposits that consumers use to smooth consumption. In the model, depositors have a claim on bank's assets with no ex-ante priority, which can only be honored sequentially. Because banks cannot satisfy massive early withdrawals, depositors are induced to run on the bank if they believe other depositors are going to do so. In that framework, a bank run is essentially a coordination failure. Beliefs about other depositors' beliefs depend on an exogenous random signal (a sunspot) that gives rise to multiple equilibria. This framework illustrates that large changes in agents' behavior may occur even absent significant changes in economic fundamentals. As a result, the individually rational actions of heterogeneous lenders generate collectively sub-optimal credit provision and entail a welfare loss.

¹²Fisher [1933] claims that between 1929 and 1933, the debt burden had increased by 40% because of deflation

¹³The Fisher and financial accelerator effect mechanisms reinforce each other in the case of demand shocks, which move prices and output in the same direction and tend to cancel each other in the case of supply shocks, which move prices and output in opposite directions.

Until the Global Financial Crisis, the modeling of financial crises had focused attention on balance-of-payments and currency crises, as an attempt to account for the wave of financial crises experienced by emerging economies in the 1980s and 1990s. The first generation of models (Krugman [1979]) focused on currency crises, whereby investors, doubtful about the government capacity to support the fixed exchange rate owing to weak fiscal space, trigger a sudden speculative attack. The second generation (Obstfeld [1996]) attributes financial crises to a mixture of deteriorating domestic conditions and shifts in expectations. However, the incapacity of the two first generations of models to account for the Mexican (1994) and the Asian (1997-1998) crises led to the adoption of a third generation of models that sets forth the interaction between excessive bank lending and currency crises (Krugman [1999]; Burnside et al. [2001]). It is only with the fourth generation of models, outlined by Krugman [2001], that the financial crisis is not first and foremost a currency crisis, but the consequences of macro-financial imbalances involving the banking sector and asset prices.

The study of financial crises has generated a vast empirical literature. Although not all financial crises generate an economic recession, 28% of recessions since 1870 in developed countries are associated with a financial crisis (Schularick and Taylor [2012]). Ng and Wright [2013] recall that in the U.S., all of the recessions over the last thirty years have had financial origins. Moreover, financial crises have been found to be more harmful than purely economic recessions (Reinhart and Rogoff [2009a]; Reinhart and Rogoff [2014]; Schularick and Taylor [2012], Jordà et al. [2013]). Jordà et al. [2015] show that in the post-WW2 period, recessions associated with a financial crisis are 22% more costly in terms of output loss than purely economic recessions. Estimation of the average output loss of financial recessions varies between 7.5% (Cerra and Saxena [2008]) and 9% (Reinhart and Rogoff [2009a]) from peak to trough and the recovery time to reach pre-crisis levels of per-capita real income is about 8 years in the post-WW2 period (Reinhart and Rogoff [2014]). Romer and Romer [2015] set forth the link between the welfare cost of financial crises and the degree of monetary and fiscal policy space prior the crisis. They find that when a country's monetary policy is not constrained at the zero lower bound and its debt-to-GDP is relatively low, the decline in output is lower than 1%, but is ten times higher when the country has none of these policy spaces.

Turning to the causes of financial crises, Reinhart and Rogoff [2009a] note that the run-up of the 20th century's "Big Five" crashes in developed economies (Spain 1977, Norway 1987, Finland and Sweden 1991, Japan 1992) were associated with a wave of financial liberalization, financial innovation, massive capital inflows ("bonanzas") and a housing boom. A common feature of most financial crises is unsustainable credit expansion (Kaminsky [1999]; Borio and Lowe [2002]; Borio and Drehmann [2009]; Mian and Sufi [2009, 2011]; Schularick and Taylor [2012]; Jordà et al. [2013, 2016]). Schularick and Taylor [2012] find that a one standard deviation expansion in real bank loan growth over the previous five years increases the probability of a crisis in the current year by 2.1 to 2.8%. Jordà et al. [2015] show that it is the growth of mortgage credit that is the riskier form of credit for future crises. By contrast, crises that are not driven by credit booms, but are instead associated with equity booms or high capital inflows, are less likely to end up in recessions. However, when asset prices interact with a

credit boom, in the form of a “leveraged bubble”, the ensuing financial crisis tend to be severe (Jordà et al. [2011]; Claessens et al. [2011]). Not all credit booms result in a financial crisis however. Gorton and Ordóñez [2016] suggest for instance that the change in productivity associated with the credit boom helps to determine whether a credit boom will be positive or detrimental for growth.

1.4 The Global Financial Crisis

The Global Financial Crisis (GFC), that sowed the seeds of the Great Recession, is not the average financial crisis. The run-up, the crisis itself and its aftermath, along with the policy intervention that followed, provide a rare natural experiment to improve our understanding of the interplay between financial and real factors. The GFC has encouraged economists to undertake a major rethinking of macroeconomic research, be it empirically owing to the amount of data collected, or for modelling purposes towards a more realistic design of the financial sector.

1.4.1 The structural causes of the crisis

The GFC is a structural crisis in the sense that it finds its roots in a number of long-term interacting factors, including financial innovation, deregulation, government support for housing ownership and loose financial conditions. Each of these factors played a role in the process of “financialisation” of the economy, that is the dramatic expansion of the financial sector relative to the real economy. Unlike the Latin American Debt Crisis of the 1980s and the Asian Financial Crisis of 1997, which took their roots in the official sector and the corporate sector respectively, the GFC originated first and foremost in the household and financial sectors.

The run-up to the crisis showed a significant expansion in household debt, especially mortgage debt, that resulted from an active political support of housing ownership for low-income families and the subsequent advent of a vast institutional framework supporting housing finance. The seeds of the unprecedented development in household finance were planted in the 1990s. In 1992, the Federal Housing Enterprises Financial Safety and Soundness Act of 1992 required that government-sponsored enterprises Fannie Mae and Freddie Mac devote a percentage of their lending to support affordable housing. After additional support under the Clinton administration, the American Dream Downpayment Act of 2003 provided grants to help lower income households to pay down payments and closing costs. As a result, the homeownership rate reached an all-time high of 69.2% in 2004, while household credit grew from 48% to 99% of GDP between 1980 and 2007.

The increase in leverage in the financial sector can be first attributed to a secular process of deregulation in the financial industry, aimed initially at increasing competition and removing barriers preventing entry. A case in point is the abolition of regulation Q in the U.S., which imposed restrictions on deposit interest rates for banks to help them attract funding, thereby restricting lending. This trend was common among developed countries. In France,

the banking reform of 1985 abolished the Treasury control over the credit market, the channelling of credit toward priority industries and subsidized bank loans, and introduced more competition in the banking sector. The deregulation of investment banking also played a pivotal role. In 1999, the Financial Services Modernization Act abolished the Glass–Steagall Act that prohibited financial institutions from performing jointly investment, commercial and insurance activities. In 2004, the Securities and Exchange Commission suspended for five major financial institutions¹⁴ the Net Capital Rule, which ensured that broker-dealers¹⁵ could meet their financial obligations. These developments allowed financial institutions to reach unprecedented levels of intra-financial leverage¹⁶.

The structural increase in debt levels is also the result of a long phase of financial deepening. First, productivity gains and progress in computational and communication technology in the financial industry allowed to increase the distance between lenders and borrowers (Petersen and Rajan [2002]) and lowered the cost of financial transactions via the standardization of financial contracts. Second, the risk management approach of the financial sector underwent a genuine conceptual Copernican revolution. The traditional actuarial long-term approach of default risk of retail banks, insurance companies and pensions funds was progressively replaced by the short-term price-driven approach of trading firms and hedge funds reflecting day-to-day opinions on the market (Dunbar [2011]). This phenomenon was accompanied by the advent of marked-to-market accounting. The price of credit is no longer an actuarial insurance premium for long-term default risk but a compensation for price risk, which may wax and wane even absent changes in the underlying real asset. Credit-default swaps (CDS), which became ubiquitous, are the epitome of this paradigm where the price of credit bears upon self-referential assessments of credit risk. The mere operating mode of the banking sector was dramatically affected by these structural changes. The “originate-to-hold” loans model was replaced by the “originate-to-distribute” loans model, in an attempt to save regulatory capital and diversify risk away. This was made possible by the emergence of securitization, whereby loans are parceled by tranching their cash flows and transferring credit risk to form asset-backed securities (ABS). The most common type of ABS was the infamous collateralized debt obligation (CDO). A typical CDO is a structured product with an equity-like tranche that absorbs losses first, a mezzanine tranche and a senior tranche. ABS are sold to non-bank financial institutions, used as collateral for short-term borrowings in the form of repurchase agreement, or transferred to off-balance-sheet vehicles. Commercial banks thereby pooled their loans into ABS, which were then sold to other financial intermediaries. The rise of securitization went hand in hand with the rise of the so-called “shadow banking system”, that purchased large amounts of CDOs, mostly made of tranches with specific ratings of Residential Mortgage Backed Securities (RMBS).

¹⁴Goldman Sachs, Merrill Lynch, Lehman Brothers, Bear Stearns and Morgan Stanley.

¹⁵Broker-dealers are companies that trade securities for customers (brokers) and for their own accounts (dealers).

¹⁶Claims by one financial firm upon another.

¹⁶Shadow banking can be roughly defined as non-banks financial intermediaries that transforms risky, long term loans in credit-risk-free short-term money-like instruments. Adrian et al. [2013a] set forth the seven steps of shadow bank credit intermediation: 1) loan origination; 2) loan warehousing; 3) pooling and structuring of loans into term asset-backed securities (ABS); 4) ABS warehousing; 5) pooling and structuring of ABS into CDOs; 6) ABS intermediation; and 7) funding in wholesale funding markets by money market intermediaries.

The joint emergence of securitization and the shadow banking sector is closely tied to the growing demand for money-like claims, i.e. safe liquid assets redeemable at par, which until then had been the sole prerogative of the banking sector (Diamond and Dybvig [1983]; Tobin and Brainard [1963]). The demand for securitized private money was first associated to the investment needs of institutional cash investors (Greenwood et al. [2015]). Institutional cash pools, that invested massively in securitized assets, offered an investment vehicle for these investors. Pozsar [2013] documents that this pools managed only \$200 million in 1990 and \$4 trillion on the eve of the crisis. The second factor is associated with the sharp development of short-term funding, for instance in the form of repurchase agreement (repo), whereby asset-backed securities are rehypothecated, i.e. used as collateral for short-term borrowing. Non-banks financial institutions rely on short-term liabilities to other financial intermediaries in order to buy financial assets and increase leverage. Even in the banking sector, part of the deposit-based funding was replaced by short-term collateralized funding. The U.S. repo market increased by 2.5 times in the four years before the crisis, reaching 30% of GDP in 2007. Other forms of short-term funding, such as Commercial Paper (CP), also experienced rapid growth over this period. The sharp development of Money Market Mutual Funds (MMFs)¹⁷ that invested in such short-term assets, also played a crucial role. As a result of these developments, from the 1980s onward, the lion's share of credit was generated outside the banking sector, by highly leveraged and unregulated non-bank institutions.

Financial innovation was expected to improve welfare by increasing the risk-bearing capacity of the economy (Rajan [2006]), either via broader participation or by enhancing market completeness. In practice however, it became apparent that not all these innovations were directed at improving the ability of the financial sector to perform its genuine social function. First, while finance can support long-run growth by channeling household savings toward corporate investment, the bulk of credit extension over that period supported consumption smoothing across the life-cycle, mostly through residential mortgage and leveraged investment in already existing financial assets. Moreover, the rise of the shadow banking sector is to a large extent associated with regulatory arbitrage aimed at concealing leverage from regulators or circumventing legal proscriptions. Philippon [2008] note that the GFC was preceded by a massive and unprecedented expansion of the financial sector in the five years preceding the financial crisis unrelated to the needs of the corporate sector, and that can therefore only be explained by the rise in housing finance and excessive risk-taking. In the words of Stiglitz [2010], “*the financial sector has become an end in itself rather than a means to an end*”.

Second, securitization and the originate-to-distribute model exacerbated opacity and agency problems. The pooling and tranching of large numbers of loans, which was initially designed to mitigate asymmetric information about the underlying assets by diversifying risk away, would later play a key role in the abrupt loss of confidence that plagued the financial system. Arora et al. [2009] for instance show that the lemon discount of Akerlof [1970]

¹⁷Money Market Mutual Funds invest in assets with a weighted average maturity of up to 60 days and seek to maintain a stable value of \$1 per share.

increases with the complexity of the CDO's structure. At the height of the financial crisis, the opaqueness of balance sheets and the widespread development of off-balance sheet instruments, made it difficult to separate the wheat from the chaff and froze funding liquidity for all financial intermediaries. Moreover, despite the promise of diversification of the originate-to-distribute model, some of the securitized loans were either pledged by banks as collateral, or kept on their balance sheet of special purpose vehicles they sponsored. Even when banks did spread the loan risk out of their portfolio, principal-agent problems related to credit risk transfer entailed more lenient due diligence, insufficient monitoring, incentives to generate fees and complete unawareness of counterparty risk. This generated both an oversupply of credit and a significant deterioration of the quality of assets geared toward securitization. According to [Ashcraft et al. \[2008\]](#), 70% of loans that did not comply with the underwriting standards of Government Sponsored Agencies ended up in securitized products in 2007. Overall, instead of increasing the risk bearing capacity of the economy, financial innovation increased systemic risk.

In parallel to the explosion of financial innovation, the scale of financial activities relative to the real economy increased significantly. [Philippon and Reshef \[2013\]](#) recall that the U.S. financial sector has grown in two waves, first from 1860 to the 1930s and then from 1950 onwards. According to the Bureau of Economic Analysis, at its peak in 2006, the financial services sector contributed 8.3% to U.S. GDP, compared to 4.9% in 1980 and 2.8% in 1950¹⁸. According to Flow of Funds data, before the GFC, the value of total financial assets was equal to ten times U.S. GDP, twice the number of 1980. While wages in the financial industry were in line with other sectors in 1980, they were 70% higher in 2007 according to [Philippon and Reshef \[2012\]](#). [Greenwood and Scharfstein \[2013\]](#) additionally find that much of the growth in finance is concentrated in the “securities”¹⁹ and the “credit intermediation” subsectors. The securities sector grew from 0.4% of GDP in 1980 to 1.7% of GDP in 2007 and the credit intermediation sector grew from 2.6% of GDP in 1980 to 3.4% in 2007, mostly in the form of mortgage household credit. Interestingly, both the securities sector and the credit intermediation sector had started to shrink on a value-added basis before the crisis, with peaks occurring in 2001 and 2003 respectively. The two subsectors are of course related, as the increase in household credit contributed to the growth of the financial sector mainly through fees on loan origination, underwriting of asset backed securities, trading and management of fixed income products and derivatives trading. On the other hand, securitization increased both the supply of subprime mortgages, by offering a wider distribution of mortgages and the demand for mortgages to securitize.

Accommodating financial conditions are an additional crucial factor underlying the steep increase in leverage and risk-taking. The first reason for loose financial conditions bears upon the structural drop in global interest rates. One prominent explanation for this relates to

¹⁸The contribution to GDP can be measured as financial sector revenues minus nonwage inputs, or equivalently as profits plus compensation.

¹⁹The securities subsector is composed of investment banks, which perform securities trading and market making, securities underwriting and asset management firms, composed of hedge funds, private equity funds and venture capital funds.

the structural break in the volatility of output and inflation that occurred in the 1980s²⁰, a phenomenon referred to as the Great Moderation, which resulted in two very long Business Cycle expansions in the 1980s and the 1990s. The most common explanation for the Great Moderation is a major shift in the conduct of monetary policy, whereby greater central bank independence and explicit inflation targeting led to a better anchoring of inflation expectations. In the U.S. for instance, before the Full Employment and Balance Growth Act of 1978 introduced the dual mandate of the Fed, the Fed’s lack of clarity produced such poor expectations of changes in the policy rate that these changes were nearly equivalent to surprises (Cook and Hahn [1989]). The increased focus on inflation is grounded on the Taylor principle (Clarida et al. [2000]), which states that the central bank can avoid a state of indeterminacy, thereby eliminating self-fulfilling expectations, by raising interest rates more than one for one with inflation. However, the fact that the Great Moderation was solely driven by enhanced monetary policy is not uncontroversial. Stock and Watson [2002b], Canova and Gambetti [2006] and Sims and Zha [2006] instead argue in favor of the “good luck” policy, in the form of smaller economic disturbances. A final possibility, known as the “structural change” story, instead argues that the propagation mechanism which translates shocks into Business Cycle fluctuations has changed in a way that leads to smaller fluctuations. Other potential sources of decline in macroeconomic volatility include the role of financial deepening on consumption and investment smoothing across states and time (Blanchard and Simon [2001]) and broader participation from riskier firms (Buch et al. [2009]), a lower contribution of inventories to output growth through better management (Cecchetti et al. [2006]) and the fact that idiosyncratic shocks, albeit more important, became less correlated across firms and sectors owing to technical progress (Stiroh [2009]; Dynan et al. [2006]).

Another explanation for loose financial conditions in the years preceding the GCF bears upon the response of the Federal Reserve to the bust of dot-com bubble, along with the adoption of new operating procedures based on gradualism, transparency and expectations management. In 2001, the Federal funds rate was cut eleven times, from 6.5% to 1.75%, and reached 1% in 2003. However, loose financial conditions are not the sole responsibility of the central bank. Even when the Fed decided to tighten monetary policy in 2004, raising the policy rate by 25 basis points at 17 consecutive meetings, this did not materialize into higher long-term rates²¹. Reasons for this include demographic factors in emerging countries inducing a preference for saving and thereby a demand for sovereign bonds of developed countries deemed safe. The mechanism at stake is set forth in Caballero and Farhi [2014] and Caballero et al. [2016, 2017], where the shortage of safe assets for countries where saving exceed investment puts pressure on long-term rates and fuels global imbalances.

Loose financial conditions were a critical element of the increase in leverage in the financial and the household sectors before the GFC, by both easing funding conditions and inducing a search-for-yield phenomena. Financial institutions were massively involved in a global “carry trade”, whereby they would borrow at a low interest rate to purchase assets with

²⁰In the U.S. for instance, the standard deviation of quarterly real GDP declined by half and the standard deviation of inflation declined by two-thirds.

²¹The so-called “Greenspan conundrum”.

higher yield, which led to a compression of risk premia across all asset classes unrelated to fundamentals (Case and Shiller [2003]). The misperception of risk, aggravated by the massive use of credit-default-swap to insure against the risk of default, muted the impact of increasing leverage. Overall, the interaction of institutional factors, financial innovation and permissive financial conditions supported a sharp increase in the leverage of the financial sector, mostly for the shadow banking system and investment banks in the U.S. and commercial banks in Europe. Overstretched balance sheets would later jeopardize the capacity of financial institutions to absorb even small losses, as liquidity concerns would quickly turn into solvency issues.

However baffling the pro-cyclicality of monetary policy and misperception of risk may seem ex-post, it is important to note that standard measures of macroeconomic sustainability failed to signal the rise of massive imbalances. First, the financial boom of the early 2000s did not lead to higher consumer price inflation as the international integration of product markets and technological advances relaxed supply-side constraints. Moreover, the imbalances manifested in non-inflationary sector misallocation of capital rather than “aggregate” capacity constraints (Borio [2014]). Second, in most countries, fiscal balances were not a source of concern. Owing to ballooning tax revenues from the construction sector, Ireland and Spain, which would later experience the most severe economic crisis, provide two quintessential examples of countries that exhibited low and falling debt-to-GDP ratios and fiscal surpluses during the financial boom.

1.4.2 The timeline

The first tremors of the GFC originated in the housing sector when U.S. housing prices started to decline on a national basis for the first time since the Great Depression. The bursting of the housing bubble and increasing interest rates prevented many subprime mortgages from being refinanced. Most subprime households, stuck with high loan-to-value and sometimes negative home equity could no longer refinance their mortgages. Delinquencies and foreclosures increased, pushing housing prices further down. Two striking facts are worth highlighting. First, the initial disruption happened in a very tiny segment of the financial sector. Dwyer and Tkac [2009] estimate that subprime mortgages accounted for 1% of global bond values, stock values and bank deposits. Second, it took almost two years for the initial loss of investor confidence in the mortgage market to propagate to other markets. The peak in housing prices occurred in 2005. By the latter half of 2006, housing starts had already plunged by more than 20% in one year, with no significant movements on the securitized markets. Losses in the subprime residential mortgages only started to materialize in August 2007 and took another few months to affect other financial markets, as the complexity of securitization undermined price discovery.

Outside the housing sector, the first hiccup of the crisis occurred on August 9, 2007, when BNP Paribas announced that it suspended its redemptions on three of its mutual funds invested in U.S. subprime mortgage debt because it could no longer value the underlying assets. In March, 2008, the investment bank Bear Stearns experienced a run and found itself unable

to refinance its short-term liabilities. None of these events, however, was sufficient to spark the firestorm. The trigger was the bankruptcy of Lehman Brothers on September 15, 2008, causing all sources of funding to the U.S. financial sector to dry up overnight, the expansion of the panic to non-mortgage credit and the abrupt cessation of securitization activities. The highly leveraged investment bank had an exposure to real estate assets that was thirty times greater than its equity, meaning that a 4% decline in these assets' value was enough to wipe out all its capital. On the very same day, the insurance company AIG had a brush with bankruptcy in the wake of Lehman Brothers' collapse. AIG had written over \$400 billion dollars of insurance contracts in the form of credit default swaps on subprime mortgage CDOs. Its short-term funding dried up instantly when it appeared that the company could not honored its commitment and AIG had to be bailed out by the Fed on September 16, 2008. The second direct casualty of Lehman bankruptcy was the Reserve Primary Fund money market fund, which held \$785 million of Lehman Brother's paper, although money market mutual funds were supposed to be a money-like safe and liquid asset redeemable at par. The collapse of Lehman Brothers triggered a run on the fund on September 16, which lost 90% of its assets as it was no longer able to redeem shares at par value. The ensuing contagion stemmed from the freeze in securitization activities. The panic on subprime mortgages and on Asset-Backed Commercial Paper (ABCP), 40% of which concerned subprimes, created a run on Money Market Mutual Funds, which were the main holders of ABCP. This run put pressure on a large scope of financial intermediaries, including commercial banks, which relied almost exclusively on short-term funding such as commercial paper and certificates of deposits held by money market mutual funds, that had to be rolled over every day to finance asset positions.

The Repurchase Agreement (repo) market also played a key role in the cross-market contagion as subprime-related assets and more generally all types of ABS could no longer be used as collateral in repo transactions. As margins increased dramatically, owing to the decline in the value of securities, and the universe of eligible collateral narrowed, the funding capacity of a large number of financial institutions that relied on short-term debt dried up instantaneously. The average haircut on repo increased from 10% at the end of 2006 to more than 40% in 2008 (Geanakoplos [2010]) when the runs on ABCP programs started. According to Gorton and Metrick [2012], from the second quarter of 2007 to the first quarter of 2009, net repo financing of U.S. intermediaries fell by about \$1.3 trillion, more than half its pre-crisis total. This "run on repo" (Gorton and Metrick [2009]) triggered a liquidity drain that played a major role in the contraction of credit (Geanakoplos [2010]). Funding and market liquidity started to interact when liquidity-constrained financial intermediaries were forced to fire-sale some of their assets to face funding and redemption pressures. This rapid unwinding process created an adverse feedback loop between falling prices and collateral constraints.

Figure 1.4 illustrates the propagation of financial stress through the lens of different U.S. financial markets. The black line is a market-traded index of the value of BBB-rated subprime mortgages. The green line represents the spread on 5-year credit default swaps for bank bonds and is a proxy for bank solvency. The blue line is the total return index for asset-backed securities made of credit card receivables unrelated to mortgage assets. The

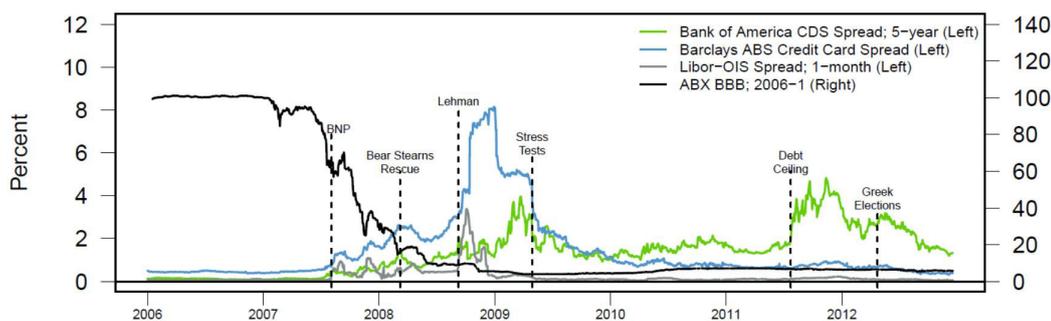


Figure 1.4: A timeline of the GFC through the lens of 4 asset prices

Source: Bernanke (2018), Brookings Institution

grey line is the one-month LIBOR-OIS spread²², which is an indicator of stress in the inter-bank lending market. The evolution of the BBB-rated subprime mortgage-backed securities index illustrates the continuous loss in investor confidence throughout 2007. As we can see, it took time for non-mortgage assets to follow suit. The first spark on non-mortgage assets occurred when BNP Paribas suspended redemptions on three of its mutual funds. Wholesale funding markets came under temporary pressure, as proxied by the LIBOR-OIS spread, but remained relatively low until September 2008, when funding pressures accentuated and spiked unprecedentedly after Lehman’s failure. The LIBOR-OIS spread remained on a high level as the U.S. government was struggling to pass the Troubled Asset Relief Program (TARP), which was eventually approved by Congress on October 3 in the form of capital injections. Evidence that the Obama administration had very limited leeway increased financial stress. Funding pressures started to ease at the end of 2008 and dropped further with the results of stress tests on the 19 largest banking institutions in February 2009. These stress tests played a key role in reducing asymmetric information and allowed these banks to raise new capital, as illustrated by the drop in credit default swap spreads. Spreads on the interbank lending market reached their pre-crisis level by May 2009. Credit spreads also began to fall, albeit at a slower pace.

The crisis did not, however, solely bears upon developments in U.S. financial markets. For many European markets, the financial crisis acted as a spark that unveiled macro-financial imbalances. One of the first casualties outside the U.S. was the U.K. bank Northern Rock in September 2007. In the early 2000s, the bank had borrowed massively on international short-term funding market to extend mortgage assets and sell securitized products on international capital markets. When confidence on securitized mortgages faded away in the summer of 2007, Northern Rock found itself unable to repay its money-market loans and became the first British bank to experience a run in 150 years. Iceland also underwent a banking crisis, owing to an excessive expansion of the banking sector based on international short-term financing in the years preceding the crisis. As the international financial crisis unfolded throughout 2007 and 2008, investors perceived the Icelandic banks to be increasingly risky. Trust in the banks gradually faded, leading to a sharp depreciation of the Icelandic króna in 2008 and increased difficulties for banks in rolling over short-term debt. In Ireland

²²The LIBOR-OIS is the interest rate on one-month interbank loans less an indicator of expected safe rates.

and Spain, lenient lending conditions from the late 1990s had sparked a self-fulfilling housing bubble. The transmission of the credit crunch to these countries in 2008 resulted in a major contraction in mortgage credit and house buildings and a dramatic decline in employment, tax revenues and consumer spending that the housing boom had underpinned.

1.4.3 Financial frictions during the crisis

Given its magnitude and the amount of data available to research programs, the GFC can be seen as a large-scale experimental laboratory to explore macro-financial linkages. Its relevance for macroeconomic research and policy design however depends on whether the crisis can be deemed peculiar by virtue of its nature or its amplitude. In that regard, [Stock and Watson \[2012\]](#) investigate whether the GFC differs from previous postwar recessions and Business Cycles. They claim that the factors associated with this crisis are not different than those associated with previous recessions and more generally with economic fluctuations since 1959. The response of economic variables to these factors is also in line with historical experience. The GFC is therefore associated to a sequence of unusually large shocks rather than changes in the stochastic macro process and can therefore legitimately serve to enhance our understanding of financial frictions.

As stated by [Christiano et al. \[2015\]](#) “*the vast bulk of movements in aggregate real economic activity during the Great Recession were due to financial frictions*”. First, it appeared clearly that most of the assumptions underlying the Modigliani-Miller theorem were proved wrong. For instance, if financial markets were perfect in the sense of Modigliani-Miller, there should be no feedbacks from the derivatives to the underlying securities. However, as shown by [Piskorski et al. \[2010\]](#), securitized loans were more likely to be foreclosed than those that remained on banks’ balance-sheet. The possibility of immediate profit above loan generation only by repackaging securities ([Shleifer and Vishny \[2010\]](#)) is an additional violation of Modigliani-Miller theorem. The most striking evidence that the Modigliani-Miller theorem did not hold in practice is that the recapitalization of banks of the 10 largest U.S. banks increased their market values by around \$100 billion more than the capital injected ([Veronesi and Zingales \[2010\]](#)).

The most prominent financial friction prevailing during the GFC is undoubtedly asymmetric information. Concerns about the exposition of counterparties to mortgage-related assets, aggravated by the complex and opaque nature of securitized products, played a crucial role in the unparalleled freeze-up of liquidity on funding markets. Because most derivatives were privately traded (over-the-counter), fears that losses on derivatives contracts would affect the counterparty’s capacity to pay back stopped dead transactions on these markets²³. By the same token, the proper functioning of the U.S. interbank market halted instantaneously, by fear that losses on banks’ derivatives trading books would affect their capacity to pay back and their capital adequacy. The first wave of state intervention therefore directly aimed at

²³In Europe, where the bulk of derivatives is traded through clearing houses with procyclical margin call supposed to mitigate counterparty risk, banks suffered less from asymmetric information.

mitigating information asymmetry in the banking sector, via bank stress tests and the Troubled Asset Relief Program.

Right from its onset, the GFC was also characterized by the magnitude of contagion mechanisms, which are key to understand how disruptions in a small segment of U.S. financial markets wreaked havoc on markets with no direct relationship with the U.S. subprime mortgage market. [Devereux and Yu \[2014\]](#) make the point clear that international financial integration helps to diversify country-specific risk, thereby reducing the severity of crises, at the cost of increasing the magnitude of cross-border spillovers and financial contagion. During the crisis, financial stress spread like wildfire to international financial markets owing to complex ramifications across markets, institutions and countries. Financial contagion may occur for a number of reasons. First, a shock to one financial market may affect the availability of credit and trading activities in other markets. In the early stages of the crisis, disruptions in the U.S. short-term debt markets created a shortage of dollars, especially for short-term funding of longer-term U.S. dollar assets and swaps for cross-currency funding. Moreover, given that U.S. financial assets represent about one third of global financial assets, portfolio losses on U.S. markets impacted significantly the balance sheet of international investors exposed to these markets. By the same token, European banks were involved in a global carry trade on U.S. financial assets ([Acharya and Steffen \[2015\]](#)), whereby they would borrow from U.S. money market funds and purchase subprime mortgages, exactly like U.S. banks²⁴. These banks were therefore forced to curb domestic lending. Second, cross-market contagion may arise via the information conveyed by a financial shock about other markets ([King and Wadhvani \[1990\]](#)). Owing to incomplete and asymmetric information, market participants are forced to base part of their decisions on the actions of other investors, thereby spurring self-fulfilling cross-market contagion. For instance, U.S. financial markets serve as a gauge for international investors, even for those which are not directly exposed to U.S. financial markets. Finally, financial contagion may also materialize through a drop in the willingness of global market participants to bear risk ([Acharya and Pedersen \[2005\]](#)). In most crises, risky assets suffer large capital retrenchment to the benefit of safe-haven assets such as the U.S. Treasuries bonds, the Swiss franc or gold. In 2008, amid heightened global risk aversion, many emerging economies faced sudden capital flow reversal, surging borrowing costs and very limited opportunities to issue equity.

Despite agreement on the importance of financial frictions to explain the unwinding of the GFC, understanding the nature of these financial frictions remains an enduring challenge. Building on the large amount of data collected during the crisis, a vast research program investigates whether financial frictions manifest themselves mainly through shocks to the demand side or to the supply side of credit, both in the run-up to the GFC and its aftermath. This question is of the utmost importance from a policy perspective to understand the credit crunch that played such a prominent role in the transmission of the financial crisis to the real sector. For instance, the legitimacy of government support to the financial

²⁴The U.S. dollar claims of European banks on U.S. borrowers increased from \$856 billion in 2002 to over \$2 trillion by 2007, mostly via the U.S. ABS market.

sector depends on whether the drop in credit to the private sector was related to heightened uncertainty about the returns of projects seeking for funds, or to banks' ailing balance sheets that prevented them from funding otherwise profitable projects.

The demand story attributes the GFC to the link between the boom and subsequent bust in housing prices and its impact on the borrowing capacity of the household sector. While the financial bubble increased the borrowing capacity of the household sector, the burst of the asset bubble and the rise in unemployment resulted in a deterioration of the creditworthiness of borrowers. In Spain, for instance, between 2000 and 2007, the share of the construction sector in GDP increased from 8% to 12,3% and the saving rate fell from 6% to 3% as consumption followed the surge in housing prices. The wealth effects associated with housing prices are, however, ambiguous. First, changes in house values also affect the rental cost and the price faced by new buyers (Buiter [2008]). A non-zero wealth effect may arise in the case of a distribution effects between agents with different marginal propensity to consume out of housing wealth. Second, only asset prices changes that are deemed permanent are likely to affect consumption. Even in that case, however, consumption smoothing over the life cycle may attenuate the short-term wealth effect on spending. Therefore, absent financial constraints, the marginal propensity to consume out of housing wealth should be relatively low. If, however, households are financially-constrained, changes in property prices should affect household borrowing and spending by somewhat more than suggested by the conventional wealth effect owing to financial accelerator mechanisms. Empirical evidence of the demand story include Mian et al. [2013], which provide clear evidence of collateral-based financial constraints and find large marginal propensity to consume out of housing wealth. Mian and Sufi [2011] show that on average, an increase in property prices support an additional borrowing equivalent to a quarter of the change in prices. This suggests that the housing bubble accounts for half of the increase in household debt between 2002 and 2006. Importantly, when lending against property outpaces credit extension, this further fuels self-reinforcing feedbacks between credit supply and asset price.

However, the assumption that the financial sector was a passive bystander of the housing bubble makes it difficult to understand the systemic impact of the GFC and the ensuing Great Recession. A requirement to understand the real aggregate effects of the GFC is therefore to admit that financial intermediaries played a pivotal role (Woodford [2010]). The credit supply view argues that the boom and subsequent bust in credit bears upon the lending capacity of the financial sector rather than changes in economic fundamentals on the demand-side. In the run-up to the financial crisis, this story implies a loosening of collateral requirements for mortgage borrowers, especially for low-income households (Duca et al. [2011]). Mian and Sufi [2009] show that the rapid expansion in the supply of mortgages loans occurred mostly in the extensive margin of credit expansion, that is towards households that were not eligible so far via more lenient lending conditions, rather than the intensive margin of homeowners borrowing against the rise in housing net worth. Lending to borrowers with low-income and poor credit quality played a prominent role in the housing bubble. Mian and Sufi [2009] therefore claim that it is the over-supply that created the housing bubble, not the opposite.

Adelino et al. [2016] argue instead that credit provision was not a driver of the housing bubble relative to the wealth and accelerator effects, on the premise that mortgage origination increased proportionally across the whole income distribution and not especially for low-income borrowers. The assumption behind the supply story regarding the crisis itself is that some of the demand for credit could not be met during the crisis owing to tighter lending conditions. One potential reason for the disruption in the normal conduct of financial intermediation is that financial institutions highly dependent on short-term wholesale funding, lacked capital to absorb the losses associated with excessive risk-taking. The contraction of aggregate output affected banks financial health by increasing non-performing loans, delinquencies and defaults on banks' balance sheets. Portfolio losses led to capital depletion, which further restricted their lending capacity. Adrian et al. [2013b] confirm that some of the demand for funds was not met during the crisis, by showing that credit-constrained firms with access to the bond market used bonds to compensate for the decline in loan supply. A vast literature also provides evidence of the bank-capital channel. Santos [2011] shows that firms borrowing from banks facing larger subprime losses paid higher spreads and received smaller amounts of credit. In addition, banks with access to large retail deposits rather than wholesale funding, cut their lending by relatively less, as might be expected in the case of capital constraints (Ivashina and Scharfstein [2010]). Carlson et al. [2013] show, however, that the bank-capital channel is non-linear and prevails for very low levels of capital. Finally, Chodorow-Reich and Falato [2017] add another channel through which bank health could affect their lending choices. While less than 10% of firms actually faced maturing bank loans during the crisis, most firms experienced tighter lending conditions because the violation of covenant²⁵ increased lenders' bargaining power and entitled them to renegotiate contract terms, to transmit rising funding cost to borrowers and to reduce their stock of loans before maturity date. Overall, it is quite difficult to make a clear-cut case that one of the two stories dominates in quantitative terms. Gertler and Gilchrist [2018] for instance show that the household balance sheet channel is important for regional variations in employment but that the disruption in the banking sector was central to the overall employment contraction.

To the extent that the management of financial frictions is very complicated once the financial crisis has erupted, a major lesson emerging from the GFC is that the Financial Cycle should be tamed right from the onset of its upward phase. Pro-cyclical bank lending amplifies the real cycle and hinders the resilience of the banking sector to adverse shocks. Over-lending in upswings is associated with the accumulation of bad loans and credit rationing during downturns. Therefore, a policy design that reduces the banking sector's pro-cyclicality helps to promote financial stability. The GFC however provided strong evidence that the prevailing macroprudential framework, enshrined in the Basel II Accords, was not suited for this purpose. Basel II for instance failed to capture exposition to securitization and off-balance sheet items, thereby leading to a large underestimation of risk in capital requirements. It also ignored the counterparty risk on over-the-counter derivatives transactions. Goodhart et al. [2004] also claims that capital adequacy requirements considerably accentuated the

²⁵Loan covenants can be defined as non-pricing terms aimed at mitigating agency problem inherent in lending contracts. Nonfinancial covenants limit the set of actions a borrower may take, while financial covenants specify thresholds for cash flow or balance sheet variables.

pro-cyclicality of the financial system. Basel III agreements, implemented from 2010 onwards, aim at addressing these shortcomings. *Inter alia*, they reinforce significantly capital requirements²⁶, augment these requirements with a countercyclical macroprudential buffer, introduce leverage and liquidity ratios and implement close supervision on Global Systemically Important Bank²⁷.

Turning to the methodological implications of the crisis, it seemed obvious, right from the onset of the GFC, that workhorse macroeconomic models were not suited to give full account of the crisis. Dynamic Stochastic General Equilibrium (DSGE) models have been especially identified as having failed not only to predict the crisis but also to anticipate its real consequences. Several observers made the claim that DSGE were inherently unsuited for the modelling of financial crises. First, the fact that most DSGE are solved as log-linear approximations around steady states *de facto* rules out non-linear discontinuous shifts that may occur in a financial crisis, such as liquidity squeezes or fire sales. Second, as stated by [Stiglitz \[2018\]](#), detrending the time series at the business cycle frequency discards non-stationary phenomena such as fluctuations in leverage that are crucial factors of financial crises. Third, the goodness of fit of most DSGE is usually grounded on second order moments, while financial crises are rare tail events that manifest in the form of skewness and fat tails into time series ([Korinek \[2017\]](#)), i.e. third and fourth moments respectively. Finally, it is technically demanding to jettison the Rational Expectation Hypothesis²⁸, although its assumptions are clearly at odds with recent developments such as the housing bubble. Because the dynamic responses of structural models necessarily reflect the modeling assumptions, first-generation workhorse DSGE models were also blamed for their unrealistic view of the financial sector. The first step towards a better understanding of modern macro-financial linkages is to recognize that the financial sector should not be confined to the banking sector. Previous research was based on the reliance of banks on deposit as the unique source of financing. Today, however, deposits account for a very small part of the banking sector liabilities and the statistics show that the fluctuations in deposits before and during the crisis were not correlated with credit supply. Moreover, bank-specific channels of transmission are based on the fundamental assumption that legal reserve requirements are a binding constraint for banks²⁹. With modern central banking practices however, reserve requirements are not a binding constraint anymore ([Bennett et al. \[2002\]](#)). Banks' special role for mitigating asymmetric information on credit markets can also be questioned. Market-based financial intermediaries provide a large proportion of credit in most developed markets, especially in times of financial crisis, where bond financing tend to serve as a substitute for bank lending ([Adrian et al. \[2013b\]](#)). [Woodford \[2010\]](#) therefore advocates for a modelling of the financial system in which the most important marginal suppliers of credit are no longer commercial banks and in which the latter

²⁶The ratio of loss-absorbing capital on risk-weighted assets

²⁷That label applies to banks based on their size, interconnection, substitutability, internationalization and complexity

²⁸The assumption that agents' expectations about the distributions of future endogenous variables coincide with the distributions predicted by the model, for which agents make no systematic mistakes. For instance, for a variable y_t and a forecasting horizon h , $E_t(y_{t+h}) = E_t(E_t(y_{t+h}|\Omega_t)) = 0$, where Ω_t includes past and current values of all variables and the structure of the economy as described by the equations of the model.

²⁹The bank-lending channel of transmission of monetary policy for instance relies on the fact that changes in the supply of reserves of commercial banks affect bank lending.

no longer rely solely on deposits as a source of funding. The reliance of banks on other sources of funding gives rise to an additional source of supply-side frictions, as uninsured funds imply credit risk and asymmetric information problems. Yet, to give credit where credit is due, the first generation of DSGE models with financial frictions already gave a prominent place to information asymmetry for Business Cycle fluctuations. What these models had not anticipated is that asymmetric information are not confined to firms and households, but would chiefly plague the lending market between financial intermediaries. A burgeoning literature has since then attempted to come up with a more realistic approach of the financial sector, where the latter is no longer a passive bystander amplifying economic developments. To this end, areas for future work include a greater consideration to state-varying risk tolerance, bounded rationality, maturity mismatches, rational individual behavior that entails greater systemic risk, or the inclusion of several financial assets that are imperfect substitutes³⁰. Seminal work in these directions include [Gertler and Kiyotaki \[2015\]](#), [Gertler et al. \[2017\]](#), to cite but a few.

³⁰Such as the the Preferred Habitat Theory of the yield curve.

Chapter 2

Halving the Financial Cycle with a non-linear Axe

2.1 Introduction

Contrary to the Business Cycle, which is commonly understood as the medium-term fluctuations of gross domestic product, the jury is still out on how to define its financial counterpart, the Financial Cycle. In a New-Keynesian world, the Business Cycle can be considered as temporary departure from the level of output that would prevail absent nominal rigidities. By the same token, the Financial Cycle could be defined as the supply of funds that would prevail absent financial frictions. [Borio \[2014\]](#) defines the Financial Cycle as “self-reinforcing interactions between perceptions of value and risk, attitudes towards risk and financing constraints, which translate into booms followed by busts”. These conceptual definitions, however, do not provide empirical guidance for the measurement of a Financial Cycle that could be studied jointly with the Business Cycle. Three different factors complicate the proper understanding and measurement of the Financial Cycle. First, we do not observe separately the demand and the supply of funds, but only the equilibrium prices and quantities. Second, a large portion of the fluctuations in financial variables are driven by the endogenous reflection of past and current economic activity, either directly or via their reaction to monetary policy. Third, bouts of euphoria or pessimism, changes in risk awareness or regulatory changes can distort momentarily or permanently the Financial Cycle. These conceptual pitfalls notwithstanding, a few studies have attempted to lay the groundwork for a better understanding of the Financial Cycle. Moreover, the choice of variables that should be included is unclear. While [Miranda-Agrippino and Rey \[2015\]](#) describe the Financial Cycle as the global co-movements of capital flows and asset prices, [Borio et al. \[2012\]](#) instead argue that “equity prices can be a distraction” and claim that the Financial Cycle is best described in terms of credit volumes and property prices.

Given these potential pitfalls, this chapter argues that the Financial Cycle should not be understood as a unique concept. Financial factors can affect economic activity in two different ways. First, a positive exogenous shock on credit can foster higher economic growth over the short to medium term, at the risk of fuelling financial imbalances and increasing

the likelihood of financial crises. Second, short-run fluctuations in financial markets affect investment and consumption expenditures via their impact on the cost of finance. These two phenomena capture different forces at different frequencies. The low-frequency component, hereinafter called the Credit Cycle, captures the co-movement of credit-like variables, while the high-frequency component will be referred to as the Financial Condition Cycle. Of course, the two concepts are not exclusive and tend to interact closely. For instance, loose financial conditions may support the accumulation of debt, as changes in asset values affect the borrowing constraints of agents looking for funds, hence affecting the equilibrium level of credit. Conversely, balance-sheet positions may impact asset prices by affecting their risk-premium component. This chapter investigates the dichotomy between the short and long-run real consequences of financial factors, which are usually studied separately in the literature.

We first document that credit and housing prices on one side and equity prices, interest rates and exchange rates on the other side, tend to be synchronized across country, therefore suggesting that we should study them separately. Then, we propose a methodology for the construction of the Credit Cycle and the Financial Condition Cycle. Instead of computing the sub-components and estimating their relationship with economic activity afterwards, they are identified in the light of their impact on economic activity. However, owing to their highly endogenous and elusive nature, estimates of the unconditional impact of financial factors on economic activity have been found to be small or inconclusive. One way to address these limitations is to study the conditional distribution of economic growth. [Adrian et al. \[2018\]](#) for instance show that the lower end of the distribution of future output growth is more closely related to financial factors than. An alternative solution, that we adopt in this chapter, is to focus on states of the world where financial constraints bind more strongly and financial factors consequently weigh more on economic activity, such as financial crises or financial stress episodes. This is done for identification purpose only and does not imply that financial factors necessarily exert an adverse impact on the macroeconomy.

Credit booms have been shown to precede deep recessions ([Jordà et al. \[2013\]](#)) and financial crises ([Schularick and Taylor \[2012\]](#)). The Credit Cycle is therefore measured as the aggregate of medium-term fluctuations in credit-like variables that convey information about future financial crises. The Financial Condition Cycle is defined as an aggregate of financial factors that affects economic growth during periods of financial stress. To ensure that our two measures of the Financial Cycle are helpful for the study of macro-financial linkages, we finally provide evidence that they contain relevant information for the real-time estimation of the state of the economy relative to its potential.

2.2 Frequency analysis

Before we dive into the in-depth analysis of the Financial Cycle, we first provide evidence of the co-movements between output and key financial variables. For the identification of peaks and troughs, we follow the turning points approach of [Bry and Boschan \[1971\]](#). We

use the turning point algorithm of [Harding and Pagan \[2002\]](#), which adapts the [Bry and Boschan \[1971\]](#) algorithm to detect turning points for quarterly time series. The algorithm selects pairs of adjacent, locally absolute maxima and minima that meet certain censoring rules. In particular, the algorithm requires the duration of a complete cycle to be of at least five quarters and the duration of each phase to be of at least two quarters. These restrictions ensure that the turning points are somewhat comparable with the NBER recession dating process. Specifically, a peak in a quarterly financial series f_t occurs at time t if:

$$\{(f_t - f_{t-2}) > 0 \text{ and } (f_t - f_{t-1}) > 0\} \cup \{(f_{t+2} - f_t) < 0 \text{ and } (f_{t+1} - f_t) < 0\}$$

Similarly, a cyclical trough occurs at time t if:

$$\{(f_t - f_{t-2}) < 0 \text{ and } (f_t - f_{t-1}) < 0\} \cup \{(f_{t+2} - f_t) > 0 \text{ and } (f_{t+1} - f_t) > 0\}$$

The algorithm first ensures that y_t is a local maximum relative to the two quarters on either side of y_t such that:

$$\{y_t - y_{t-2} > 0, \Delta y_t > 0, \Delta y_{t+1} < 0, y_{t+2} - y_t < 0\}$$

Once the turning points are computed, one way to quantify the synchronization between time series is to study turning points clustering. We use the concordance index of [Harding and Pagan \[2002\]](#), which represents the average number of periods in which two variables are at the same phase of the cycle. The series are perfectly procyclical (countercyclical) if the concordance index is equal to one (to zero), while a value of 0.5 indicates the lack of systematic relationship. The concordance index between x and y , c_{xy} is computed as:

$$c_{xy} = \frac{1}{T} \sum_{t=1}^T [s_{x,t}s_{y,t} + (1 - s_{x,t})(1 - s_{y,t})]$$

with

$$s_{x,t} = \begin{cases} 1 & \text{if } x \text{ is in expansion in } t \\ 0 & \text{otherwise} \end{cases}$$

The statistical significance of the concordance indexes can be computed as follows ([Harding and Pagan \[2002\]](#)):

$$c_{xy} = 1 + 2\rho_{s_x, s_y} \sigma_{s_x} \sigma_{s_y} + 2\mu_{s_x} \mu_{s_y} - \mu_{s_x} - \mu_{s_y}$$

where μ_{s_i} , σ_{s_i} and ρ_{s_i, s_j} are the empirical average and standard deviation of s_i and the empirical correlation between s_i and s_j , respectively. As a result, c_{xy} and ρ_{s_x, s_y} have the same statistical significance. ρ_{s_x, s_y} can be estimated with the following linear relationship, estimated with robust regression to account for potential serial correlation in the residuals:

$$\left(\frac{s_{y,t}}{\sigma_{s_y}} \right) = \alpha + \rho_{s_x, s_y} \left(\frac{s_{x,t}}{\sigma_{s_x}} \right) + \varepsilon_t$$

We compute the concordance between GDP, credit-to-GDP, total credit, property prices, stock prices and the exchange rate with the U.S. dollar¹. Our sample consists of 17 developed countries. Credit and property data come from the BIS, the other variables come from Thomson Datastream. All variables are considered in level. Credit, property prices and stock prices are deflated by the Consumer Price Index.

Table 2.1 displays the average concordance index for all countries between 1982Q2 and 2017Q4. Country-specific [concordance tables](#) and [turning points](#) are available in the appendix.

Table 2.1: Concordance table

	gdp	property	credit-to-gdp	credit	equity	exchange rate
gdp	1	0.69	0.66	0.77	0.67	0.47
property		1	0.69	0.66	0.59	0.45
credit-to-gdp			1	0.8	0.52	0.54
credit				1	0.56	0.52
equity					1	0.52
exchange rate						1

The concordance index suggests that credit, credit-to-GDP and property prices exhibit rather synchronized phases and tend to co-move with output. Stock prices are less synchronized with credit variables and property prices. Finally, the exchange rate follows somewhat independent turning points. Based on the intuition provided by these results, we will first study jointly credit variables and property prices.

2.3 The Credit Cycle

The Credit Cycle waxes and wanes as the result of demand and supply factors. On the supply side, the balance sheet conditions and capital requirements of financial intermediaries affect their capacity to supply credit. On the demand side, fluctuations arise from changes in investment opportunities and expected income. A negative income shock, for instance, may force firms and households to deleverage and to scale back investment and consumption. Additionally, borrowers may also face constraints on the quantity or the price of credit when their net worth is deemed insufficient to mitigate asymmetric information. Credit allows economic agents to make choices about whether to bring forward or defer spending and should thereby boost investment and consumption in the short term. However, as shown by Fisher [1933] and Minsky [1982], leverage that is not backed by robust income flows can fuel unsustainable growth and lead to a financial crisis. Higher level of debt means that borrower's capacity to repay their debt becomes increasingly sensitive to economic conditions and interest rates. If expected profit fails to realize, or if the economy falls into a recession, borrowers are unable to service debt, which in turn makes the financial sector more fragile and impede its lending

¹For the United States we use the DXY Index, which is the value of the United States dollar relative to a basket of U.S. trade partners' currencies.

capacity. Hence the conventional view that credit may be positive for growth in the short term, but weigh on long-term growth (Kindleberger [1978], Reinhart and Rogoff [2009a]). Drehmann et al. [2017] use the database of Drehmann et al. [2015] to show that the serial dependence of the debt-service ratio² is the main channel whereby new borrowings affect the probability of financial crises. In the short run, new borrowings have positive effects and the debt-service does not increase. But because debt-service is a function of the stock of debt outstanding, which continues to grow even after new borrowings peak, the ratio keeps increasing even after the peak. After a financial bust, it takes time for debt-service ratios and thus spending, to normalize even if interest rates fall, as principal still needs to be paid down.

The aim of that section is to compute a proxy of the Credit Cycle that accounts for the link between leverage and financial imbalances. Intuitively, Credit Cycle peaks should coincide with episodes of financial crises. We first select credit-like variables which may serve as early-warning indicators of financial crises at different horizons. These variables are then aggregated to compute a proxy for the Credit Cycle.

2.3.1 Data

The universe of candidate variables to measure the fluctuations of credit at the aggregate level is relatively undisputed in the literature. The inclusion of credit quantities is self-explanatory given that the aim of the Credit Cycle is to capture the build-up of financial imbalances associated with aggregate leverage. We also consider the credit-to-GDP ratio on the premise that it is a good early warning indicator of banking crises (Borio and Lowe [2002]).

However, the fact that not all credit booms lead to a financial crisis (Mendoza and Terrones [2008]) suggests that credit quantities are not sufficient statistics to capture financial imbalances. Asset prices could complement the signal provided by credit variables, via their impact on collateral, or as a recipient of credit flows in the case of credit-driven financial bubbles. A vast literature emphasizes the interaction of credit and asset prices and the build-ups of financial risk (see, for instance, Jordà et al. [2015, 2016]). Gourinchas et al. [1999] and Mendoza and Terrones [2008] show that credit booms are associated with periods of rising stock prices and a real appreciation of the exchange rate. Claessens et al. [2012] and Claessens et al. [2011] provide empirical evidence that recessions associated to asset bubbles busts tend to be deeper and longer.

The results of our concordance analysis suggest that property prices exhibit a higher degree of synchronicity with credit variables than stock prices, which tend to be more volatile. The focus of property prices also hinges on strong theoretical underpinnings. In models where agents are constrained by how much housing collateral they can pledge against their

²The debt-service ratio is the ratio of interest payments plus amortizations to income. It relates the burden of debt (interest plus principal) to the income flows such as wages or profits used to service the debt of the private sector.

borrowings, changes in housing prices generate booms and busts in the Credit Cycle (Iacoviello [2005]). Empirical results also indicate that a large part of borrowings is secured by real estate, for both households and firms. Another reason for including housing prices is that excess credit may first materialize as excess demand on the housing market (Igan and Loungani [2012]).

Data on credit, credit-to-GDP and property prices is available at a quarterly frequency from the Bank for International Settlements. Credit is defined as the outstanding amount of credit to the private non-financial sector at the end of each quarter. For property prices we focus on residential property prices. We would like to include the debt-service ratio on the grounds that it provides insight on the sustainability of debt and the vulnerability of balance sheets to changes in interest rates. However the dataset of the Bank for International Settlements only starts in 1999, which is too restrictive for our analysis. By the same token, we would like to include a measure of leverage of the banking system and of market-based financial intermediaries such as broker-dealers, given their prominent role in recent financial events. Again, owing to data constraints, both across time and in the cross-section, and the rare occurrence of financial crises, we are not able to include these measures of leverage without losing too many degrees of freedom.

Credit and property prices are considered in logs and deflated by the Consumer Price Index. Because the two series are integrated of order one, they enter the model as year-over-year growth rates. The series are then filtered to isolate the components that are the most relevant for predicting financial crises. We use the band-pass filter of Christiano and Fitzgerald [2003] and specify the filter in order to isolate fluctuations with a duration comprised between 32 and 120 quarters, which corresponds to four times the frequency of the Business Cycle commonly accepted in the literature. This calibration is consistent with the historical average duration between two consecutive financial crises (Borio et al. [2012]) and the fact that the Credit Cycle is longer than the Business Cycle (Claessens et al. [2012]). Figure 2.1 shows credit (blue), credit-to-GDP (red) and residential property prices (green) after the appropriate transformations.

2.3.2 Computing the Credit Cycle

Computing the impact of credit-like variables on economic activity is a complicated task owing to endogeneity and the non-linear nature of this relationship, as mentioned in the introductory chapter. Because there is overwhelming evidence that leverage can be destabilizing for long-term growth, we focus on specific events where these adverse effects are more likely to materialize. Banking crises appear as a natural candidate to proxy for financial imbalances given their costly and long-lasting impact on output (Cecchetti et al. [2009]; Jordà et al. [2011, 2013]). Corporate debt crisis, on the contrary, are less relevant for the question at hand given their minor effect on aggregate activity (Giesecke et al. [2014]). In addition, bank health can potentially reinforce macro-financial linkages under capital requirements rules (Gerali et al. [2010]; Meh and Moran [2010]). We use the banking crises database of

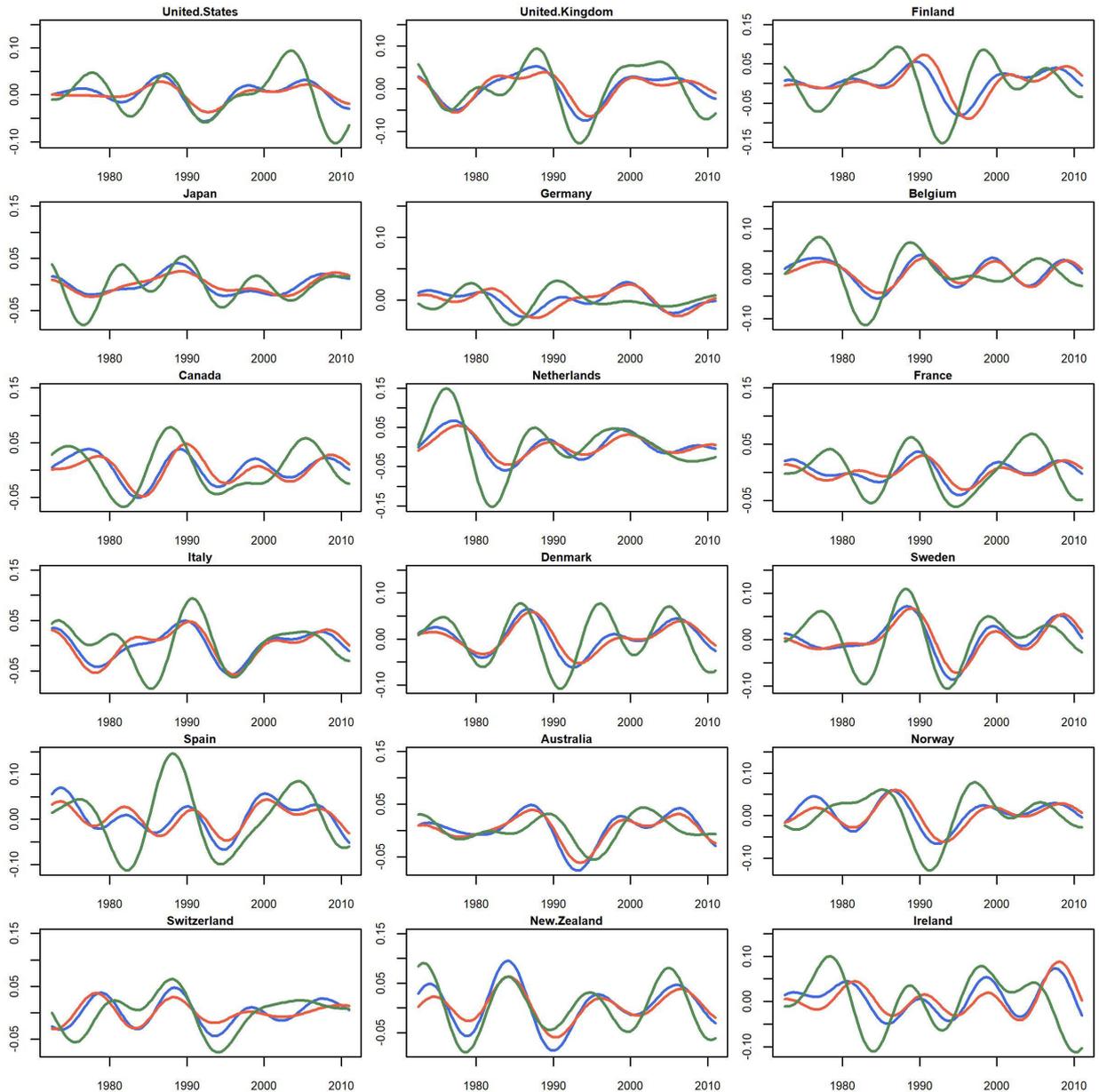


Figure 2.1: Filtered financial variables

Babecky et al. [2012], which offers the advantage of being available at a quarterly frequency between 1970 and 2010. Banking crises are identified by aggregating information from several influential papers³. A banking crisis is defined qualitatively⁴ and corresponds to episodes of financial stress in the banking system, in the form of bank runs, losses or bankruptcy, and public policy interventions to support the banking sector. Table 2.2 displays the number of occurrence of banking crisis in the sample and Figure 2.2 is a heatmap that displays in red the occurrence of banking crises for each country.

³Caprio and Klingebiel [2003]; Detragiache and Spilimbergo [2001]; Kaminsky [2006]; Kaminsky and Reinhart [1999]; Laeven and Valencia [2008, 2010, 2012]; Levy-Yeyati and Panizza [2011] and Reinhart and Rogoff [2011]

⁴as opposed to the quantitative definition of financial crises of Frankel and Rose [1996] or Lo Duca and Peltonen [2013], to cite but a few.

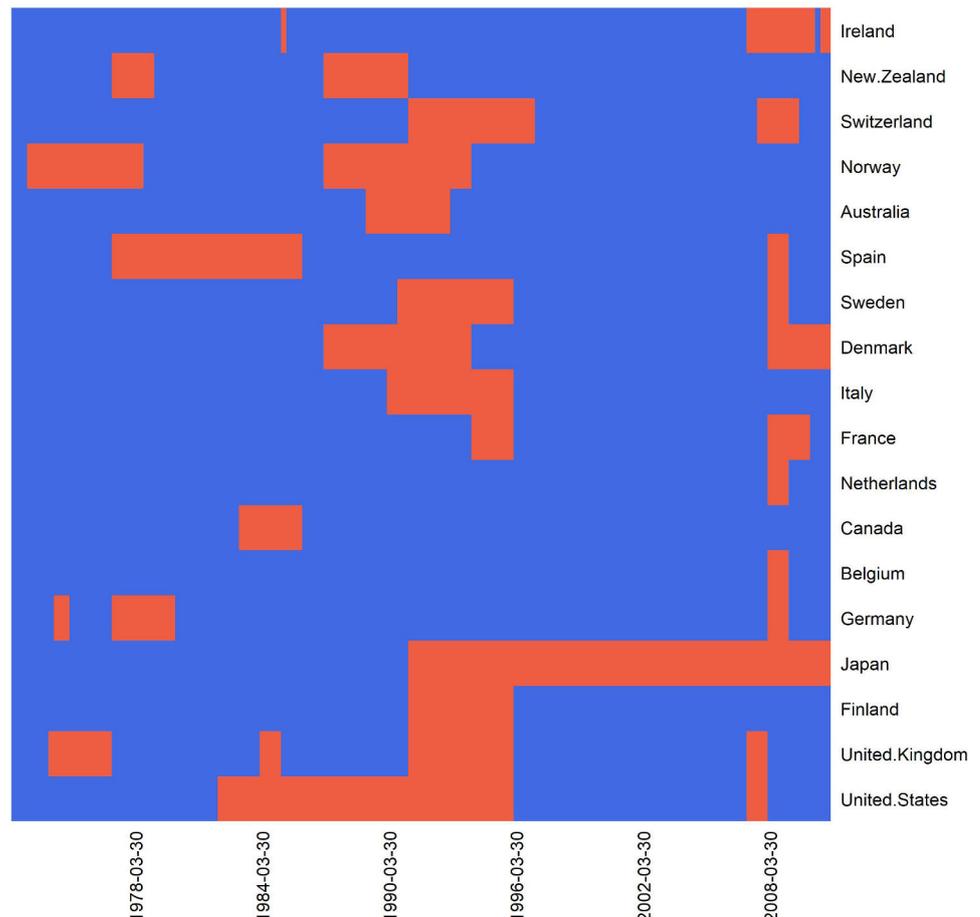


Figure 2.2: Heatmap of banking crises

Table 2.2: Number of crisis events

	US	UK	FN	JP	DE	BG	CN	NE	FR	IT	DN	SW	SP	AU	NW	CH	NZ	IR
nb. of crisis events	60	40	20	80	19	4	12	4	16	24	40	26	40	16	50	32	24	16
nb. of crisis sequences	2	4	1	1	3	1	1	1	2	1	2	2	2	1	2	2	2	3

Our sample covers 18 countries⁵, from 1971Q2 to 2010Q4, owing to limitation on the banking crises database. We motivate the inclusion of individual variables in the Credit Cycle by testing their marginal predictive power for the prediction of banking crises. To this end, we use a binary classification model to predict the occurrence of banking crises.

Figure 2.3 illustrates the average evolution of credit, credit-to-GDP and housing around banking crises episodes. Interestingly, the three financial variables share the same tendency to be very high relative to their historical mean in the run-up of a banking crisis and to drop significantly below their historical mean after the crisis.

⁵Australia, Belgium, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, United Kingdom, United States.

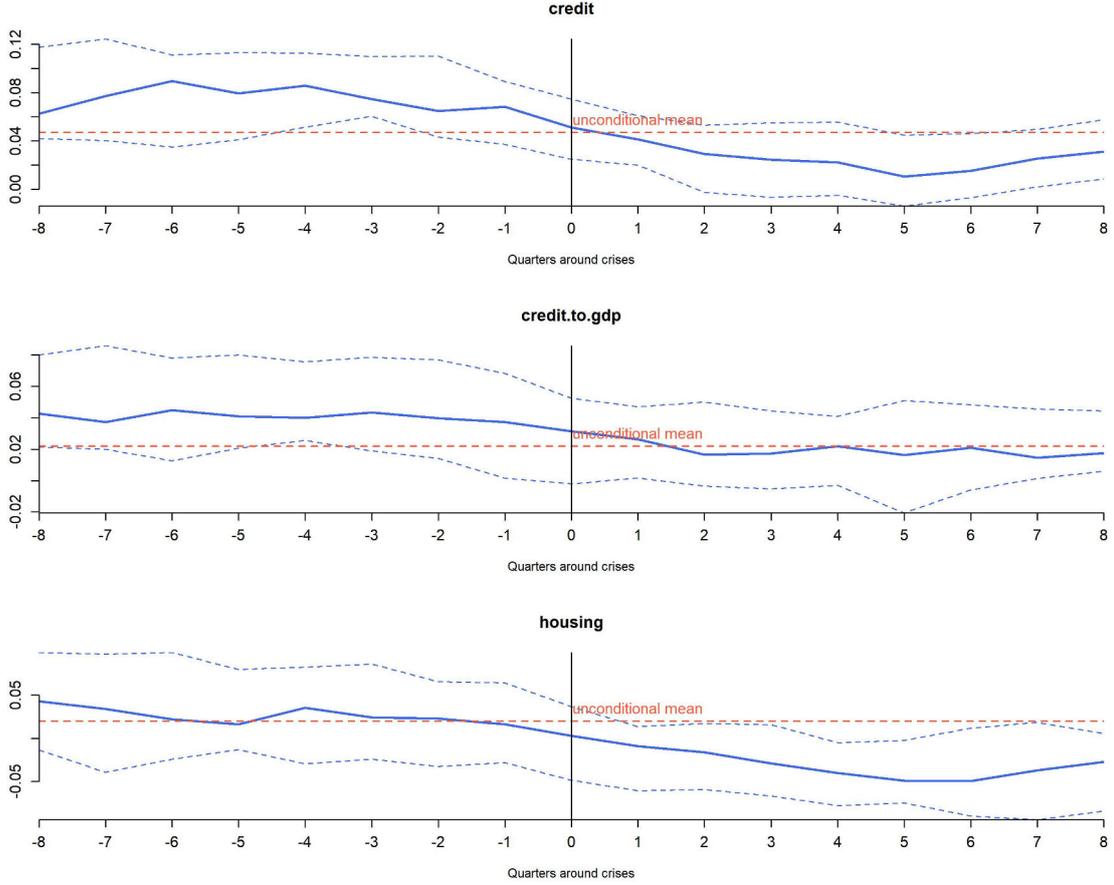


Figure 2.3: Evolution of financial variables around banking crises

Via a dynamic pooled Logit model with unobserved heterogeneity, we then model the probability to be in a banking crisis $Y_{i,t+h}$ at horizon h for country i as a function of p lags of the dependent variable and q lags of the financial variable of interest $X_{i,t}$:

$$\mathbb{P}(Y_{i,t+h} = 1 | X_{i,t}, \dots, X_{i,t-q}, Y_{i,t-p}, \dots, Y_{i,t}) = F(\tau_i + Z_{i,t} + \varepsilon_{it}), \quad \text{with } \varepsilon_{i,t} \sim \mathcal{N}(0, 1)$$

where τ_i is an unknown intercept representing the i -th country specific effect. F is assumed to be a logistic cumulative distribution function⁶ and:

$$Z_{i,t} = \alpha + \beta_0 X_{i,t} + \dots + \beta_q X_{i,t-q} + \gamma_0 Y_{i,t} + \dots + \gamma_p Y_{i,t-p}$$

where $\alpha, \beta_0, \dots, \beta_q, \gamma_0, \dots, \gamma_p$ are assumed to be the same for all countries. We treat the individual effects τ_1, \dots, τ_n as nuisance parameters; or incidental parameters, and compute the pooled estimator by maximum likelihood, as suggested by Heckman [1987].

Omitting country-specific subscript for simplicity, the likelihood of the pooled model is

⁶ $F(x) = e^x / (1 + e^x)$.

the following:

$$\begin{aligned}\mathcal{L}(\theta) &= \mathcal{L}(Y_{1+h} = y_{1+h}; \dots; Y_{T+h} = y_{T+h}; \dots; Y_{1+h} = y_{1+h}; \dots; Y_{T+h} = y_{T+h}) \\ &= \prod_{t=1}^T F(Z_t)^{y_{t+h}} (1 - F(Z_t))^{1-y_{t+h}}\end{aligned}$$

with $\theta = (\beta_0, \dots, \beta_q, \gamma_0, \dots, \gamma_p)$. And the log-likelihood is:

$$\log \mathcal{L}(\theta) = \sum_{t=1}^T \left[y_t \ln(F(Z_t)) + (1 - y_t) \ln(1 - F(Z_t)) \right]$$

The estimator $\hat{\theta}$ is estimated by maximizing the log-likelihood, such that:

$$\hat{\theta} = \arg \max_{\theta} \log \mathcal{L}(\theta)$$

The model is estimated for $h = 1, \dots, 8$, for each financial variables and for all combinations of these variables. For each model, the number of lags of the dependent and the independent variables is chosen based on a set of information criteria. We first estimate the regressions with all the lags, select only the ones that are statistically significant at a 10% nominal level and re-estimate a more parsimonious model.

One way to assess the predictive performances of a classification model beyond in-sample goodness-of-fit is to train the model on a subset of the sample and to test its accuracy on the remaining dataset, a procedure called cross-validation. Cross-validation helps to find a compromise between in-sample goodness-of-fit and proper out-of-sample generalization. In the case of a classification problem, however, out-of-sample accuracy is not a sufficient statistic as it depends on the balance between the two categories⁷. Moreover, the Logit classifier provides a probability of financial crises but the threshold to make binomial forecasts from a real-valued classifier still has to be defined. This threshold will affect the balance between “true positive” (a banking crisis is predicted by the model and does happen in actual data) and “false negative” signals (a banking crisis is predicted but does not occur). A very high threshold would miss most banking crisis events (type I errors), but would make very few false positive signals (type II errors), while a low threshold would do the opposite. A common method in the literature is to assume specific preferences of the policymaker regarding the trade-off between type I and type II errors. For instance, [Borio and Drehmann \[2009\]](#) assume that the policymakers’ preference is to minimize the noise-to-signal ratio (the ratio of false alarms to correctly predicted events) while capturing at least two-thirds of the crises. Instead of calibrating this threshold arbitrarily, which is beyond the scope of this chapter, we compute the Receiver Operating Characteristic (ROC) curve, which maps for a continuum of thresholds value between 0 and 1, the proportion of true positive against the proportion of false positive signals. Accuracy is measured by the Area Under the ROC curve (AUC). An area of 1 represents a perfect test, while an area of 0.5 represents a worthless test. As a rule of thumb, AUC values exceeding 0.75 are usually deemed to reflect useful prediction performances.

⁷For instance, if the unconditional probability of financial crises is 1%, a classifier that always predicts an absence of crisis would be mechanically 99% accurate.

Table 2.3: Predictive power for banking crises according to AUC

	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8
AR(4)	0.856	0.820	0.781	0.741	0.721	0.699	0.672	0.638
credit-to-gdp	0.970	0.949	0.926	0.901	0.890	0.875	0.864	0.848
housing	0.966	0.938	0.902	0.858	0.835	0.795	0.775	0.768
credit	0.964	0.936	0.912	0.884	0.873	0.859	0.849	0.828
credit-to-gdp + housing	0.976	0.956	0.934	0.911	0.894	0.879	0.867	0.857
credit + housing	0.974	0.950	0.924	0.899	0.884	0.870	0.856	0.843
credit + credit-to-gdp	0.971	0.955	0.934	0.910	0.899	0.888	0.870	0.855
credit-to-gdp + housing + credit	0.976	0.956	0.934	0.910	0.900	0.880	0.868	0.855

To come up with a more robust measure of the AUC statistic, we randomly generate a large number of train/test splits for which we compute the average out-of-sample AUC. The AUC statistic is computed for models including different combinations of the three financial variables, with 4 lags of the banking crisis indicator. [Table 2.3](#) displays the AUC statistic for each model specification and for all forecasting horizons from one to eight quarters.

Our results suggest first that autoregressive terms account for a large proportion of the models' predictive power. We are interested in the marginal predictive power of financial variables, above and beyond the information content of lags of the endogenous variables. Overall, we find that property prices and credit exhibit strong predictive power up to one year, that deteriorates at further horizons. Moreover, the inclusion of credit, credit-to-GDP and property prices increases significantly the predictive power of our model relative to models with only one predictor. Importantly, the predictive power does not vanish across the prediction horizon, which is all the more important that the detrimental effects of the Credit Cycle may take time to materialize. The model with credit-to-GDP and property prices and the model that includes the three variables display similar predictive performances. For the sake of parsimony, we only include credit-to-GDP and property prices in our Credit Cycle.

[Figure 2.4](#) illustrates the ROC curve for the selected model. The horizontal axis represents 1 minus the specificity, that is, the percentage of non-crisis observations classified as crisis by the model. The vertical axis represents sensitivity, which is the proportion of actual banking crisis correctly classified as crisis by the model. Above the 45-degree line, for every cut-off value the true-positive rate is higher than the false-positive rate. A random classifier would have a ROC curve that lies along the 45-degree line, meaning that for every cut-off value, the true-positive rate is exactly equal to the false-positive rate.

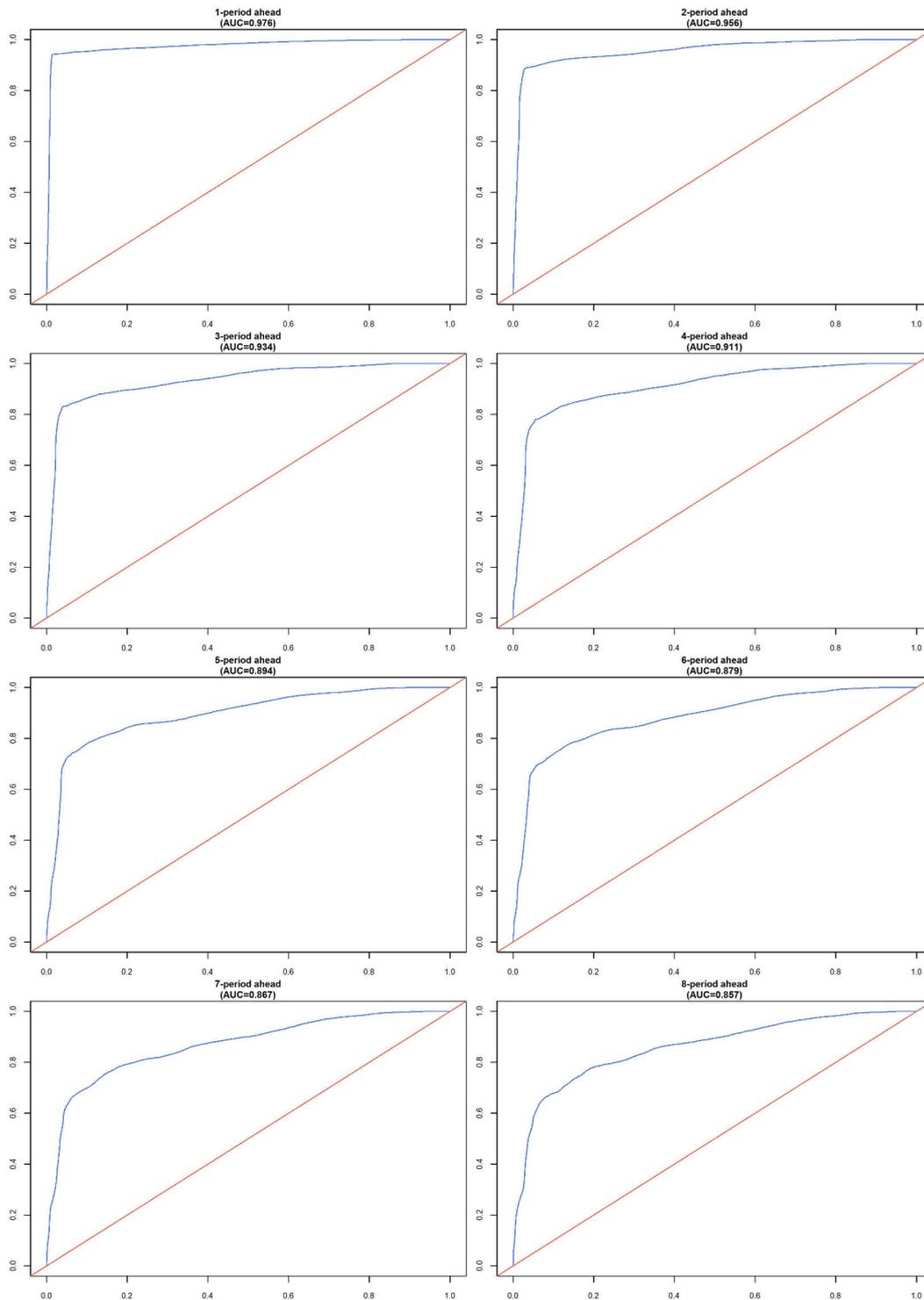


Figure 2.4: AUROC plots for the final model including credit-to-GDP and housing prices

We finally build our Credit Cycle as the average of the filtered housing and credit-to-GDP series. For each country, [Figure 2.5](#) illustrates the Credit Cycle (blue) along with the year-over-year growth rate of GDP filtered with the Christiano-Fitzgerald filter at the standard Business Cycle frequency (red).

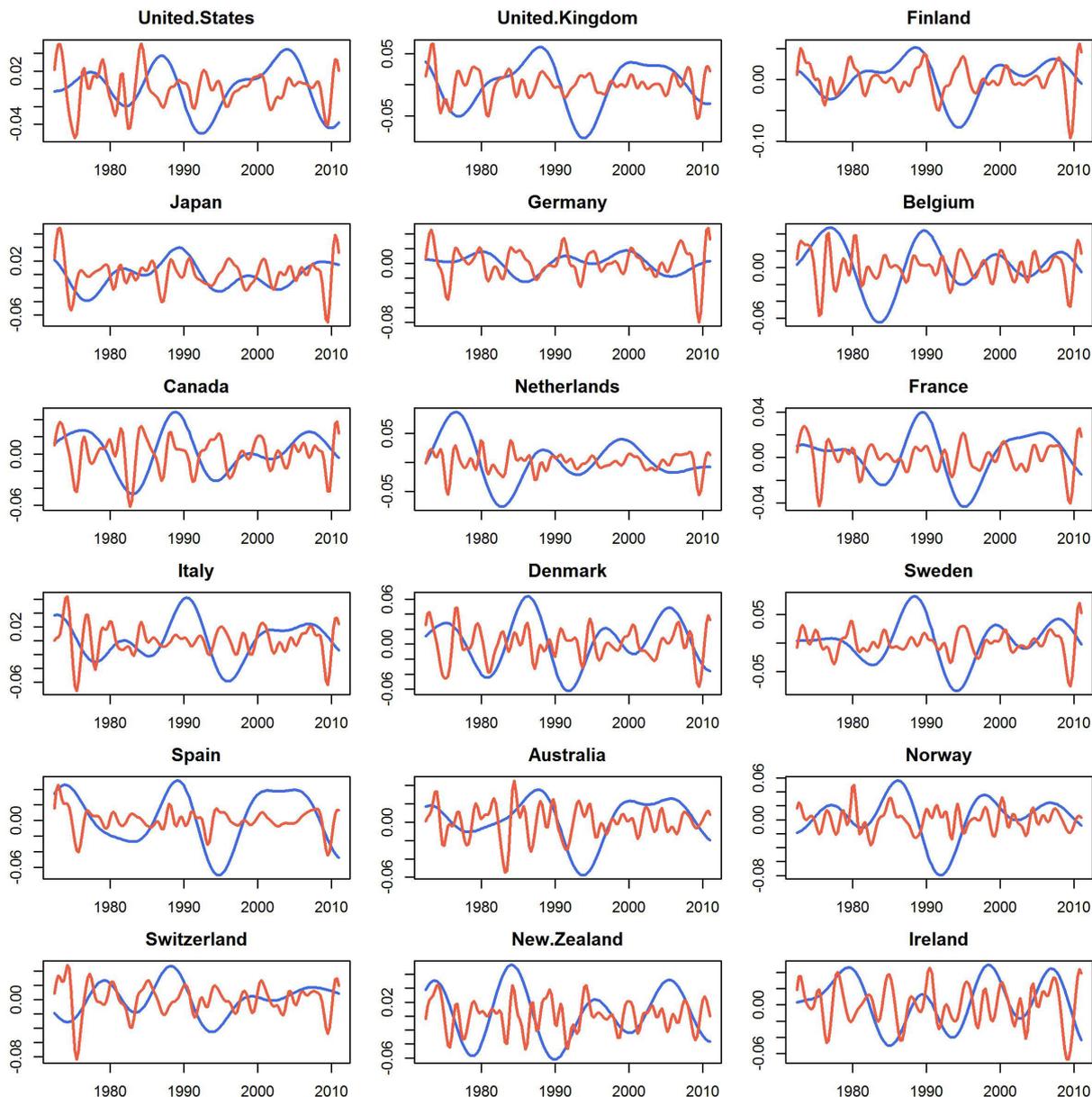


Figure 2.5: Credit Cycles and cycle component of GDP growth

2.4 The Financial Condition Cycle

In addition to the long-run impact of the Credit Cycle on the macroeconomy, financial factors can affect the short and medium-term dynamics of growth via fluctuations in financial conditions. Financial conditions can be understood as the current state of financial variables, including prices, quantities, stock and flow variables, that influence economic activity. Intuitively, financial conditions summarize the general cost and availability of funding, to raise new funds, in the form of debt or equity, or to refinance existing liabilities. They may also reflect the channels of transmission of financial factors to the real sector⁸. As developed in the introductory chapter, neoclassical channels include the interest-rate channel for investment and consumption and the financial wealth channel. Non-neoclassical channels of transmis-

⁸See [Hatzizi et al. \[2010\]](#) for a very comprehensive discussion of the issues.

sion instead arise in the presence of financial frictions on the demand and the supply side of the credit market when the Modigliani-Miller theorem does not hold. Additionally, financial conditions may affect economic activity via the risk-taking channel, whereby changes in risk-aversion push financial intermediaries to adjust their leverage (Borio and Zhu [2011]; Adrian and Shin [2006]), or via the impact of financial stress on aggregate uncertainty.

A major reason why financial conditions are worth monitoring is that, contrary to the assumption of most macro-models, the policy rate is not, more often than not, a sufficient indicator of the conditions at which economic agents can access funding. Very few real decisions depend directly on the policy rate. Instead, they depend on interest rates corresponding to the horizon of the underlying spending decision and embed a term premium and a borrower-specific risk premium. If financial conditions moved predictably with the policy rate, the latter would be a sufficient summary. Yet, the response of financial conditions to the policy rate is unstable and unpredictable, even along the sole yield curve. For example, the effect of the monetary tightening cycle of the mid 2000s by the Fed⁹ on financial conditions was more than offset by the decline in long-term yields, narrower credit spreads and rising stock prices. In particular, long-term rates, which matter for spending decisions, did not increase much over the period owing to a smaller term premium. By the same token, the sharp drop in the Federal Funds rate during the GFC was not enough to offset the sharp increase in credit spreads and the negative wealth effects of plummeting asset prices. Even for short-term borrowing, the policy rate is not always an adequate measure of money market lending conditions. Variables such as the TED-spread¹⁰ may mirror financial conditions more faithfully. Reasons for such a discrepancy between the policy rate and overall financial conditions include psychological factors, the reaction of domestic financial conditions to global factors, or portfolio rebalancing effects related to fluctuations in investors risk-aversion and demand for safe assets.

Given the loose relationship between the policy rate and overall financial conditions, a recent strand of the literature argues that the central bank should augment its policy rule to target a broader set of financial variables than the sole policy rate. Curdia and Woodford [2010] show that augmenting the Taylor rule (Taylor [1993]) with other financial prices could improve significantly the economy's response to disturbances to the supply of intermediation. Taylor et al. [2008] for instance proposed to include the LIBOR-OIS¹¹ in the Taylor rule. The recent adoption of unconventional monetary policy tools such as asset purchases or forward guidance can be seen as an extension of the central bank mandate to broader financial conditions.

In practice however, measuring the impact of financial conditions is technically challenging. First, to be useful for policy analysis, financial conditions should be purged from the

⁹Starting in June 2004, the FOMC raised the target by 25-basis-point at 17 consecutive meetings, from 1.0% to 5.25%.

¹⁰The TED-spread is the difference between the interest rates on interbank loans and on short-term government debt of the same maturity.

¹¹The LIBOR-OIS is the interest rate on one-month interbank loans less an indicator of expected safe rates.

endogenous reflection of past and current economic prospects on financial variables. In particular, if the lion's share of financial condition's fluctuations was endogenous, there would be no reason to study their real impact, as past economic activity itself would contain all the relevant predictive information. An additional requirement for measures of financial conditions to be helpful for policy analysis is that only persistent movements should be considered, insofar as high-frequency fluctuations are unlikely to have real consequences. Additionally, the signal provided by financial variables is state-dependent. For instance, as recalled by [Chari et al. \[2008\]](#) during the GFC, movements in interest rate spreads may be informative about the cost of borrowing during normal times, but not necessarily during financial stress episodes, as economic agents are likely to postpone spending or look for alternative sources of funds. Moreover, the impact of changes in financial conditions most likely depends on the level of financial variables. For instance, in the model with heterogeneous financial intermediaries of [Coimbra and Rey \[2017\]](#), a decrease in interest rates stimulates investment and increases financial stability when the level of interest rates is high, but decreases financial stability when it is low. Finally, movements in financial conditions may be ambiguous as they capture both demand and supply factors. Consider, for instance, that a rise in corporate spreads provoked by an increased demand for borrowing may indicate a boost in investment and a future economic expansion. On the other hand, a rise in corporate spreads arising from the supply side of credit is more likely to signal a future economic slowdown.

These theoretical limitations notwithstanding, it has been remarkably difficult to uncover significant effects of financial factors in macroeconomic time-series data ([Kashyap and Stein \[1994\]](#); [Hubbard \[1998\]](#)). The contention of that chapter is that this is related to the episodic nature of this relationship. In normal times, the economy is driven by real factors and the investment decision of the firm is based on the expected return relative to the cost of capital. Financial conditions are a passive bystander of the real side. In this case, financial conditions can potentially affect the ex-post return on equity but do not motivate investment in the first place. In the words of [Bernanke et al. \[2007\]](#), “healthy financial conditions help a modern economy realize its full potential”. When financial conditions deteriorate or depart significantly from their steady state value, however, they affect economic activity more than what a linear relationship would suggest, forcing agents to cut back on spending, financial intermediaries to tighten lending conditions and investors to run away from risky assets. In that case, “adverse financial conditions may prevent an economy from reaching its potential” ([Bernanke et al. \[2007\]](#)). Such financial stress episodes may be related to heightened uncertainty, liquidity constraints, or sudden shifts in risk-aversion.

The non-linear nature of macro-financial linkages has generated a vast literature. On the theoretical side, the regime shift may result from occasionally binding borrower constraints ([Arellano and Mendoza \[2002\]](#)), borrower default ([Dubey et al. \[2005\]](#)), limited commitment in financial contracts ([Lorenzoni \[2008\]](#)) or endogenous financial risk and fire sales. Empirical work suggests that increasing financial stress typically leads to sharp downturns in economic prospects ([Brave and Butters \[2012\]](#)) and that this relationship arises when financial stress exceeds a certain threshold ([Hollo et al. \[2012\]](#)). In a Markov-Switching VAR framework,

Hartmann et al. [2015] show that financial shocks have larger variance and stronger transmission to macroeconomic variables in periods of financial stress. Likewise, Lhuissier [2017] shows that disruptions in financial intermediation trigger adverse effects for the real economy only during financial stress events.

Financial Condition Indexes (FCI) are an attempt to provide a unique proxy for broad financial conditions. FCI are then typically used for forecasting purposes (Hatzius et al. [2010]) or in order to study the impact of financial shocks in Structural VARs (Darracq-Paries et al. [2014]). The typical FCI includes quintessential variables such as short and long-term interest rates, bank lending volumes, stock prices, credit conditions and the exchange rate. Candidates indicators for more refined measures of financial conditions include the TED-spread, credit spreads (Curdia and Woodford [2010]), leverage (Adrian and Shin [2008a]), bank lending surveys (Lown and Morgan [2006]) or banks' non-core liabilities (Shin and Shin [2011]), to cite but a few. As far as the aggregation method is concerned, several approaches have been considered. Ideally, we would like each component to be weighted according to its relative impact on economic activity and to avoid double-counting (for instance short term rates may affect activity via their impact on long-term rates in addition to their direct impact). However, this is relatively unfeasible in practice. One strand of the literature uses weights derived from reduced-form models such as a simple IS curve that relates the output gap to asset prices and a Phillips curve linking the output gap to inflation (Mayes and Virén [2001]; Gauthier et al. [2003]). A related literature uses elasticities estimated via small-scale VARs (Swiston [2008], Beaton et al. [2009]), where the weights correspond to the reaction of GDP to a one-unit standard deviation shock on a financial variables once other financial variables are controlled for. A final approach, that we follow, uses data reduction techniques to aggregate a large set of financial variables (Angelopoulou et al. [2014]; Darracq-Paries et al. [2014]; Hatzius et al. [2010]; Brave and Butters [2011]).

Most of the literature on financial conditions first computes the FCI and then studies its impact on the macroeconomy. We instead adopt a data-driven approach grounded on the episodic nature of the interplay between financial conditions and economic activity. The premise of our identification method is that the impact of financial conditions on the Business Cycle should be stronger during financial stress episodes when financial constraints bind more and are more likely to weigh on economic activity. In the spirit of Galvão and Owyang [2013], which identifies financial stress as periods where exogenous financial shocks have stronger negative effects on economic activity, we define financial conditions as financial factors that exhibit the non-linear correlation with output suggested by the long line of studies on macro-financial linkages. This built-in mechanism ensures that only the financial variables that affect economic activity in times of financial stress will be included in our Financial Condition Cycle. We first compute factors on a large dataset of U.S financial variables and then use a Markov-switching model to identify the factors that corresponds to the definition of financial conditions outlined herein.

2.4.1 Data

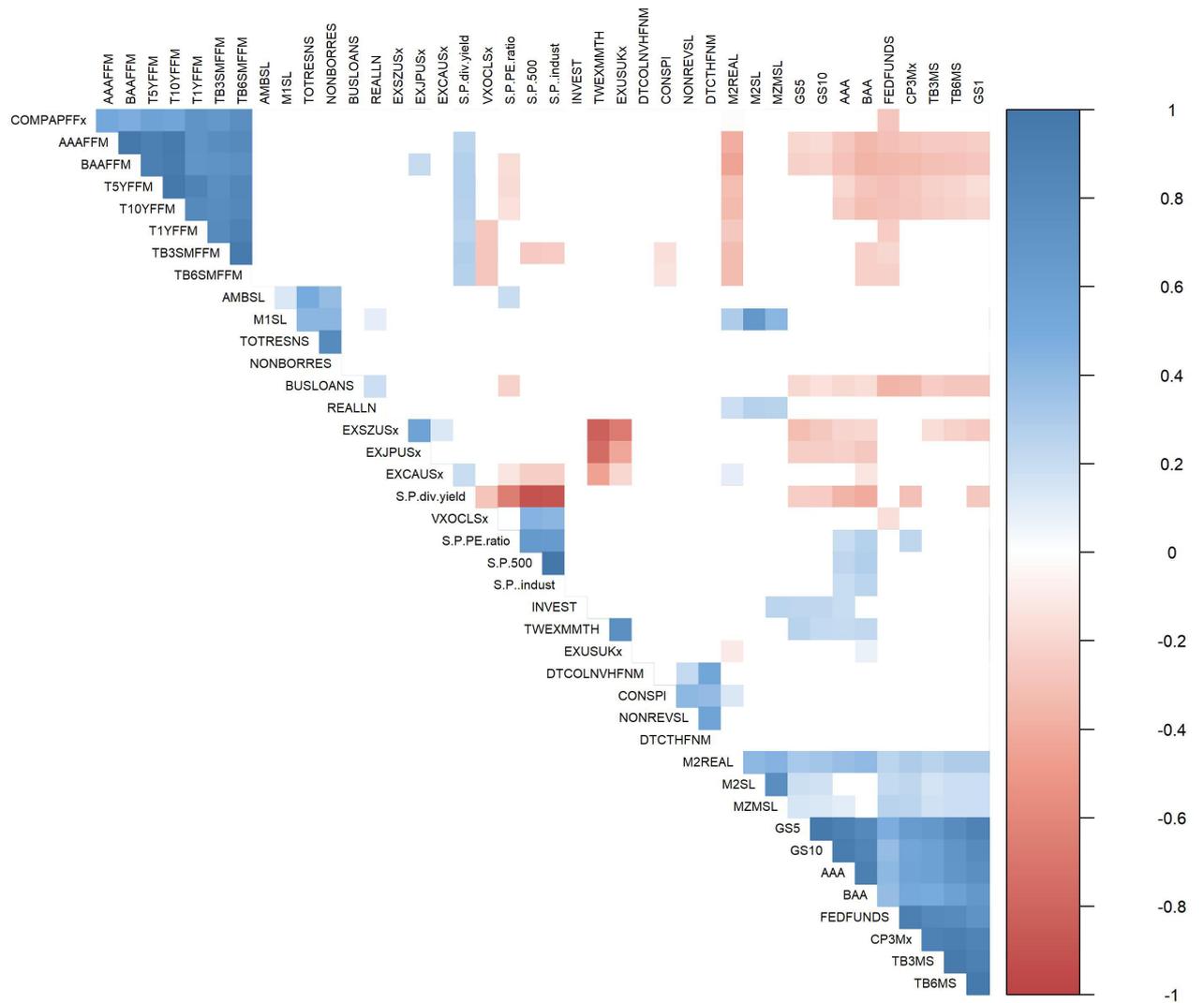
Contrary to the Credit Cycle, which was parsimonious by nature due to the strong comovement of credit-like variables at the domestic level, the universe of non-redundant financial variables that potentially plays a role for financial conditions is large. We therefore consider a large number of financial variables and adopt a data-driven agnostic selection process. The rationale for the inclusion of both price and quantity variables is that the two can be complementary. If, for instance, financial institutions engage in credit rationing to limit their exposure to moral hazard as in [Stiglitz and Weiss \[1981\]](#), shifts in the supply of funds may materialize via changes in the quantity of credit rather than the interest rate, the latter no longer being a reliable indicator of the cost of funds. Additionally, even if the cost of credit increases when the economy slows down, the quantity of credit may paradoxically increase due to the procyclicality of firms' cash flows.

Owing to data availability constraints, we restrict our analysis to the United States for the sample to be long enough to encompass several financial stress episodes. To avoid the burden of handling changes in definitions and revisions, we use the Fred-MD U.S. macroeconomic database of [McCracken and Ng \[2016\]](#), which includes monthly data starting from 1962. Among the 134 monthly variables of the dataset, we extract the 41 variables that can be deemed "financial". These variables encompass several financial markets such as money supply, the credit market, interest rates, exchange rates and the stock market.

The data is transformed at a quarterly frequency to make it comparable to GDP. Since the raw data is already available in seasonally-adjusted form, we do not make any additional adjustments for seasonality. Following [Stock and Watson \[2005\]](#) outliers are defined as observations of the stationary series with absolute median deviation larger than three times the interquartile range. Identified outliers are removed and replaced with the median value of the preceding five observations. We then transform each variable to make it stationary. The transformation undergone by each variable can be found in [Table 2.4](#). All series are then standardized to have a zero mean and unit variance to ensure that they do not influence unduly the aggregate index. [Figure 2.6](#) shows the correlation between the transformed variables.

Table 2.4: Selected financial variables and data transformation

Code	Variable	Transformation
Money and Credit		
M1SL	M1 Money Stock	Second difference of logarithm
M2SL	M2 Money Stock	Second difference of logarithm
M2REAL	Real M2 Money Stock	First difference of logarithm
AMBSL	St. Louis Adjusted Monetary Base	Second difference of logarithm
TOTRESNS	Total Reserves of Depository Institutions	Second difference of logarithm
NONBORRES	Reserves Of Depository Institutions	First difference of growth rate
BUSLOANS	Commercial and Industrial Loans	Second difference of logarithm
REALLN	Real Estate Loans at All Commercial Banks	Second difference of logarithm
NONREVSL	Total Nonrevolving Credit	Second difference of logarithm
CONSPI	Nonrevolving consumer credit to Personal Income	First difference
MZMSL	MZM Money Stock	Second difference of logarithm
DTCOLNVHFNM	Consumer Motor Vehicle Loans Outstanding	Second difference of logarithm
DTCTHFNM	Total Consumer Loans and Leases Outstanding	Second difference of logarithm
INVEST	Securities in Bank Credit at All Commercial Banks	Second difference of logarithm
Interest rates and FX		
FEDFUNDS	Effective Federal Funds Rate	First difference
CP3Mx	3-Month AA Financial Commercial Paper Rate	First difference
TB3MS	3-Month Treasury Bill:	First difference
TB6MS	6-Month Treasury Bill:	First difference
GS1	1-Year Treasury Rate	First difference
GS5	5-Year Treasury Rate	First difference
GS10	10-Year Treasury Rate	First difference
AAA	Moody's Seasoned Aaa Corporate Bond Yield	First difference
BAA	Moody's Seasoned Baa Corporate Bond Yield	First difference
COMPAPFFx	3-Month Commercial Paper Minus FEDFUNDS	Level
TB3SMFFM	3-Month Treasury C Minus FEDFUNDS	Level
TB6SMFFM	6-Month Treasury C Minus FEDFUNDS	Level
T1YFFM	1-Year Treasury C Minus FEDFUNDS	Level
T5YFFM	5-Year Treasury C Minus FEDFUNDS	Level
T10YFFM	10-Year Treasury C Minus FEDFUNDS	Level
AAAFFM	Moody's Aaa Corporate Bond Minus FEDFUNDS	Level
BAAFFM	Moody's Baa Corporate Bond Minus FEDFUNDS	Level
TWEXMMTH	Trade Weighted U.S. Dollar Index: Major Currencies	First difference of logarithm
EXSZUSx	Switzerland / U.S. Foreign Exchange Rate	First difference of logarithm
EXJPUSx	Japan / U.S. Foreign Exchange Rate	First difference of logarithm
EXUSUKx	U.S. / U.K. Foreign Exchange Rate	First difference of logarithm
EXCAUSx	Canada / U.S. Foreign Exchange Rate	First difference of logarithm
Stock market		
S&P 500	S&P's Common Stock Price Index: Composite	First difference of logarithm
S&P: indust	S&P's Common Stock Price Index: Industrials	First difference of logarithm
S&P div yield	S&P's Composite Common Stock: Dividend Yield	First difference
S&P PE ratio	S&P's Composite Common Stock: Price-Earnings Ratio	First difference of logarithm
VXOCLSx	VXO	Level



2.4.2 Computation of the financial factors

As suggested by [Miranda-Agrippino and Rey \[2015\]](#), financial variables tend to exhibit strong correlation relationships. This is confirmed by [Figure 2.6](#). For the aggregation of financial variables, we therefore adopt a method capable of handling a large set of potentially correlated data. Factor models are ideally suited in the case at hand. They offer the advantage of avoiding having to choose arbitrarily the financial variables and to deal with potential collinearity. The main assumption is that many variables may be driven by a small number of common unobservable driving forces. Factor techniques allow to break down the variations in the data into those that are pervasive, which constitute the factors, and those that are idiosyncratic and may provide a wrong signal. We thereby estimate a small number of latent factors that best capture the cross variance in our financial dataset. The static factor model expresses each of the time series as a common component Λf_t driven by the factors, plus an idiosyncratic disturbance term e_t , such that:

$$X_t = \Lambda F_t + e_t,$$

where X_t is a vector of N stationary observed variables, F_t is an r -dimensional vector of unobserved common factors and r is typically much smaller than N . Λ is a $N \times r$ matrix of factor loadings. Finally, e_t i.i.d $\sim (0, \Sigma_e)$ is an N -dimensional vector of uncorrelated idiosyncratic components such that Σ_e is diagonal. When the noise terms are mutually uncorrelated, that is, $E(e_i f_j) = 0$ ($\forall i, j$), and when both factors and noise terms have zero mean, the model is said to be a strict factor model.

The estimation of the static factor model is done with the Principal Components method of [Stock and Watson \[2002a\]](#). The principal components are estimated by least squares. They represent the optimal linear combination of X_t . The principal component estimator of the factors consistently estimates F_t up to a pre-multiplication by an arbitrary non-singular $r \times r$ matrix. The estimation therefore yields the space spanned by the factors, rather than the factors themselves. A classic solution to pin down uniquely the factors, that we follow here, is to impose the arbitrary restriction that $\Lambda' \Lambda = I_r$. Because our panel is unbalanced, we use the Expectation-Maximization algorithm to find the least squares solution. Missing observations are initialized to zero, which is the unconditional mean because the data has been demeaned. The missing value for series k at time t is updated to $\hat{\lambda}'_k \hat{f}_t$. Then, the data is demeaned and standardized again and the factors and loadings are re-estimated from the updated panel. The iteration stops when the factors estimates are relatively stable.

The number of factors r is selected according to the criterion of [Bai and Ng \[2002\]](#) by minimizing the sum of squared residuals while keeping the model parsimonious, such that:

$$r = \arg \min_r \left(\ln(\hat{V}_r) + r \cdot g(N, T) \right), \quad \text{with} \quad \hat{V}_r = \frac{1}{NT} \sum_{i,t} \hat{e}_{t,i}^2,$$

where \hat{V}_r is the average residual variance when r factors are estimated, g is a penalty function and N and T are the cross-section and time dimensions of the panel. This criterion suggests

eight factors in our dataset. The 8 estimated factors account for 75% of the variation in the data. [Figure 2.7](#) represents the factors and their proportion of explained variance and [Figure 2.8](#) shows how the factors load on each variable.

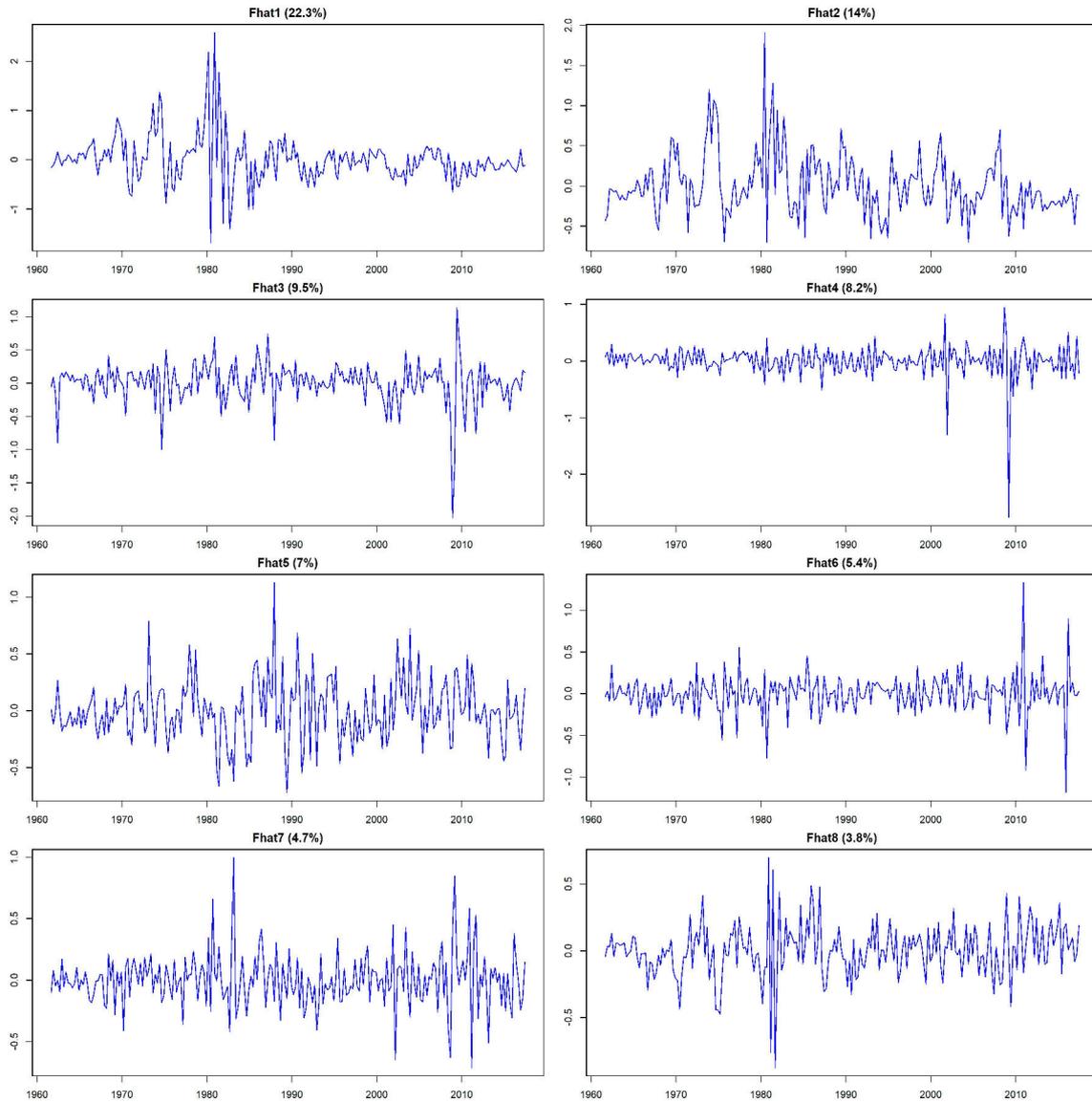


Figure 2.7: Factors and variance explained

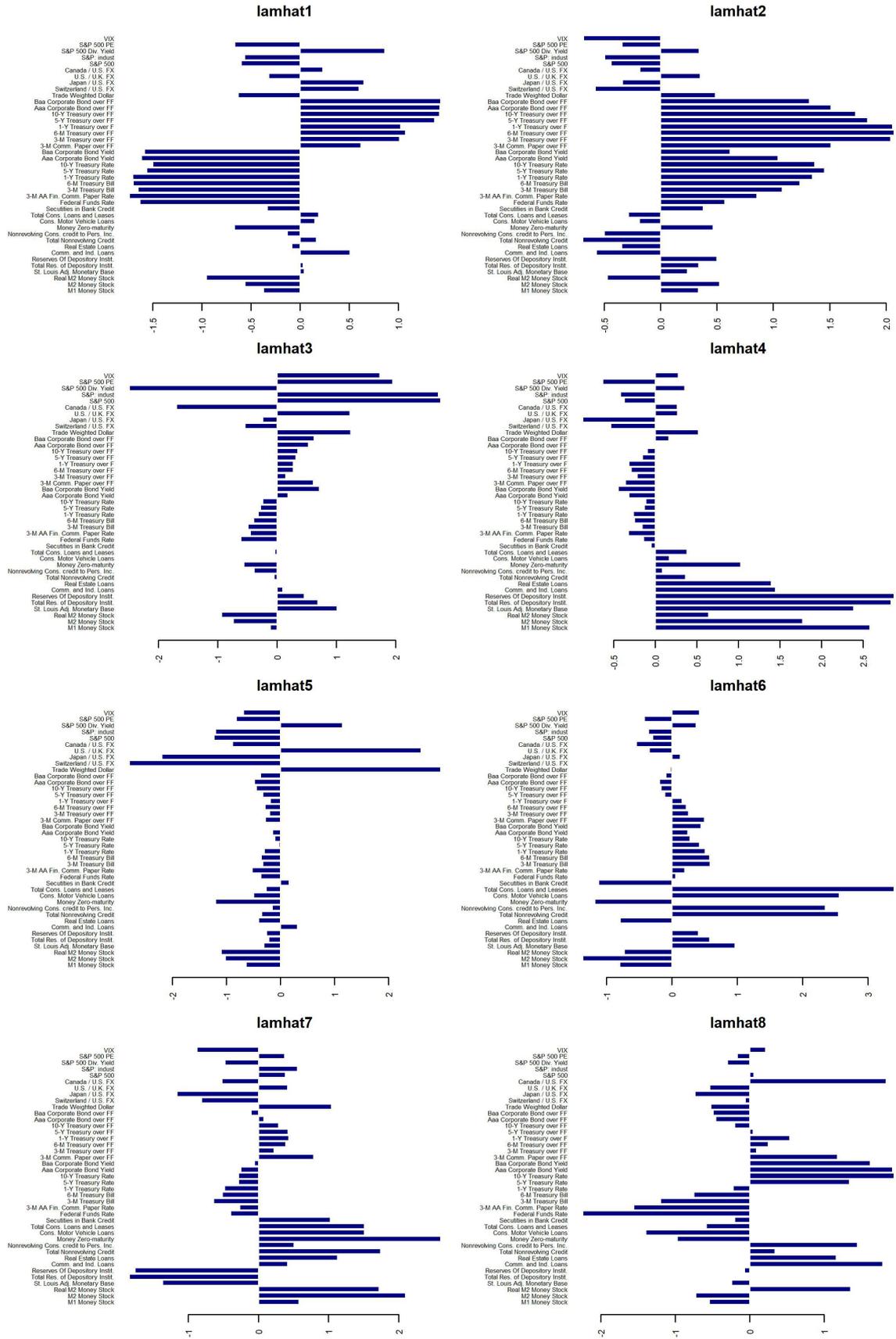


Figure 2.8: Factor loadings

In order to interpret the factors, we compute the incremental explanatory power of the estimated financial factors. Assuming that the factors are ordered from 1 to 8, we define $R_{i,j}^2$ as the R^2 of the regression of variable i ($i = 1, \dots, 41$) on factors 1 to j ($j = 1, \dots, 8$). Then the incremental power of factor j on variable i is given by $R_{i,j}^2 - R_{i,j-1}^2$ for $j = 2, \dots, 8$ and $R_{i,1}$ for $j = 1$. Table 2.5 lists the ten series with the highest incremental explanatory power for each factors.

Table 2.5: Top 10 variables with the highest incremental predictive power

Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
CP3Mx	TB6SMFFM	S&P 500	NONBORRES	TWEXMMTH	DTCTHFNM	MZMSL	FEDFUNDS
GS1	T1YFFM	S&P: indust	TOTRESNS	EXSZUSx	DTCOLNVHFNM	M2SL	GS10
TB6MS	TB3SMFFM	S&P div yield	M1SL	EXUSUKx	NONREVSL	TOTRESNS	AAA
TB3MS	T5YFFM	S&P PE ratio	AMBSL	EXJPUSx	CONSPI	NONBORRES	EXCAUSx
FEDFUNDS	T10YFFM	VXOCLSx	M2SL	S&P 500	M2SL	NONREVSL	BUSLOANS
AAA	COMPAPFFx	EXCAUSx	BUSLOANS	S&P: indust	MZMSL	M2REAL	BAA
BAA	AAAFFM	TWEXMMTH	REALLN	MZMSL	INVEST	DTCOLNVHFNM	CP3Mx
GS5	GS5	EXUSUKx	MZMSL	S&P div yield	AMBSL	DTCTHFNM	CONSPI
GS10	GS10	AMBSL	EXJPUSx	M2REAL	M1SL	AMBSL	DTCOLNVHFNM
BAAFFM	GS1	M2REAL	M2REAL	M2SL	REALLN	EXJPUSx	M2REAL

The first factor explains 22% of the variation in the financial dataset and seems to capture the comovements between interest rates, as its incremental explanatory power is mostly associated with these variables. This factor exhibits negative loadings on the policy rate and bond yields and positive loadings on bond yield spreads over the policy rate, which suggests that the spread component of bond yields (the term premium plus the risk premium) and the interest rate component tend to move in opposite directions, especially for long-term bonds. This may additionally suggest that monetary policy is “leaning against the wind” relative to bond prices. Factor 2 contributes to 14% of the variance and is also largely dominated by measures of spreads on the credit market. It loads positively on the policy rate, bond yields and bond yields spreads, thereby supporting the Expectations Hypothesis of the term structure of interest rates, which links interest rates across all maturities. Factor 3 explains 9% of the variance and captures comovements on the stock market, on which it loads positively. The negative loading on the dividend yield reflects the fact that the ratio shrinks mechanically when the denominator, stock prices, increases without a corresponding increase in dividends. In addition, the negative loading on the exchange rate with Canada and the positive loading on the exchange rate with the U.K. suggest that equities perform better when the dollar depreciates with respect to their trade partners, or when capital flows in from global financial centers such as London. Reciprocally, the positive loadings on the Trade Weighted Dollar suggest that good equity performances attract capital flows and drive the dollar up. As expected, the Japanese Yen and the Swiss Franc, which are considered as safe-haven currencies, tend to depreciate relative to the dollar when the U.S. stock market is doing well, reflecting a decrease in global risk aversion. Overall, an increase in this factor is consistent with an easing of financial conditions, for instance related to financial wealth effects. Factor 4 explains 8% of the common variance in the data and is dominated by measures of money supply such as M1 and M2 money stocks or the reserves of depository institutions, on which it exhibits positive loadings. Factor 5 explains 7% of the common variance and is dominated by exchange rate variables. Factor 6 accounts for 5% of the common variance and is dominated by credit

variables such as Total Consumer Loans. It exhibits positive loadings on loans quantities, interest rates and spreads, and does not load on the policy rate, meaning that the spread of interest rate component drives interest rates up when the volume of credit rises, potentially suggesting an increase in risk premia attached to higher leverage. Factor 7 explains a bit less than 5% of the variance and illustrates the negative correlation between interest rates and credit quantities, which is consistent with a downward sloping loan demand curve. Finally, factor 8 explains 4% of the variance in the financial dataset and exhibits positive loadings on long-term bonds and corporate bond yields and negative loadings on short-term rates. This factor therefore accounts for changes in the term spread between long-term and short-term rates. A reduction in the term spread, called a yield curve bull flattening when it arises from an increase in short-term rates, and a bear flattening when it arises from a drop in long-term rates, is known to be a harbinger of recession. The first reason is that it signals either poor future economic conditions via the long end of the yield curve or a monetary tightening via its short end. The second reason is that a flatter yield curve dampens the profitability and the lending capacity of the banking sector which relies on maturity transformation. An increase in this factor corresponds to a steepening of the yield curve and is therefore akin to an easing of financial condition, all other things being equal.

In order to focus on exogenous shifts in financial conditions, we purge our financial factors from economic developments. Let F_i denote the i^{th} financial factor and y_t denote GDP quarter-on-quarter growth rate. The factors are purged individually with current and lagged values of GDP growth as follows:

$$F_{i,t} = A_i(L)y_t + f_{i,t}$$

where $A_i(L)$ is a lag polynomial of order 4 and the f_i are the “exogenous” financial factors.

2.4.3 Construction of the Financial Condition Cycle

Now that we have reduced the dimension of the financial dataset, we could aggregate the financial factors by weighting them according to their respective proportion of variance explained. However, not all financial factors are equally important for growth. For instance, as suggested by the limited real implications of the stock market crash of 1987 or the dot-com crash, “equity prices can be a distraction” (Borio [2014]). In order to focus on events where the financial sector has real impacts, we require that the financial factors correlates with economic activity in times of heightened financial stress. We build a data-driven selection process whereby only financial factors that affect adversely and significantly economic activity during financial stress episodes are included in the Financial Condition Cycle. We assume the existence of at least two regimes, a normal regime and a regime of financial stress where the feedback from the financial factors to the real economy are stronger. If the transition between the two states were deterministic, we could estimate a regression model with a dummy variable signaling financial stress. However, this would require to use an extraneous source of information to gauge financial stress. Instead, we prefer to let the data speak and

identify the two regimes with a Markov-switching model and check ex-post that the smoothed probabilities correspond to standard financial stress episodes. The Markov-switching algorithm assumes that the transition between the two regimes is stochastic, i.e. tends to occur abruptly and unpredictably. The conditional distribution of economic activity depends on a latent state, which evolves through time as a discrete Markov chain. Such models allow to introduce switches in the autoregressive dynamics, in volatility and in the correlation structure between variables. As shown by [Hamilton \[1989\]](#), this type of model is able to identify recessionary events by itself. When adding our financial covariates however, the model with only two regimes no longer identifies recession events because it fails to account for the Great Moderation structural break of the mid-1980s. Instead of adding a time dummy for the Great Moderation, we include a third regime. The implicit assumption behind this is that the sensitivity of economic activity to financial variables has changed in the 1980s, which is supported by a vast literature. The model with three regimes is capable of identifying recession events as in [Hamilton \[1989\]](#), which is the cornerstone of our identification strategy. Among the three regimes, we identify the financial stress regime based on the concordance between the probabilities of being in this state and financial stress episodes. Because Financial Stress Indexes such as the Kansas City Financial Stress Index, the Saint Louis Fed Financial Stress Index or the Chicago Fed’s National Financial Conditions Index, are not available on a long time span, we use NBER recessions as a proxy for financial stress. A “stress event” is thereby defined as a period where the latent Markov states follows the same cyclical pattern than economic recessions. This identification scheme yields similar conclusions in terms of the selected financial stress regime when the financial stress indexes mentioned above are used on shorter samples.

We assume that the conditional probability density of the economic variable y_t is given by:

$$p(y_t|f_{t-1}^k, s_t) = \begin{cases} f(y_t|f_{t-1}^k, \theta_1) & \text{if } s_t = 1 \\ f(y_t|f_{t-1}^k, \theta_2) & \text{if } s_t = 2 \\ f(y_t|f_{t-1}^k, \theta_3) & \text{if } s_t = 3 \end{cases}$$

where y_t is the growth rate of GDP, f^k is one of the financial factors estimated previously ($k = 1, \dots, 8$), and θ_1 , θ_2 and θ_3 are vectors of parameters. In order to mitigate the endogeneity bias arising from potential simultaneity between financial factors and economic activity, the financial factors are included with a lag. For a given regime, the model is assumed to be linear, as follows:

$$y_t = \begin{cases} \alpha(s_1) + \beta(s_1)f_{t-1}^k + \sigma(s_1)\varepsilon_t & \text{in regime } s_1 \\ \alpha(s_2) + \beta(s_2)f_{t-1}^k + \sigma(s_2)\varepsilon_t & \text{in regime } s_2 \\ \alpha(s_3) + \beta(s_3)f_{t-1}^k + \sigma(s_3)\varepsilon_t & \text{in regime } s_3 \end{cases}$$

where ε is assumed to be standard, normal, independent and identically distributed. For a given regime s_t , economic activity is generated by the following process:

$$E[y_t|f_{t-1}^k; s_t] = \alpha(s_t) + \beta(s_t)f_{t-1}^k$$

The states s_1, s_2 and s_3 follow a first-order Markov process, meaning that the next period's regime depends on the current regime only. The transition from one state to the other follows the following probability:

$$p_{ij} = P(s_{t+1} = j | s_t = i, s_{t-1} = k, \dots; I_t, I_{t-1}, \dots) = P(s_{t+1} = j | s_t = i)$$

where p_{ij} is the probability of being in state j in t conditional on being in state i in the previous period. p_{ii} is a measure of the intra-regime persistence when in regime i (typically $p_{ii} < 1$). The average duration of regime i is $(1 - p_{ii})^{-1}$ and the unconditional probability of being in regime k is given by:

$$P(s_t = k) = \frac{1 - p_{ii} - p_{jj}}{2 - p_{kk} - p_{ii} - p_{jj}}, \quad \text{with } k \neq i \neq j$$

In a three-regime model, the knowledge of at least six transition probabilities is sufficient to describe the full transition process, since:

$$\begin{pmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{pmatrix} = \begin{pmatrix} p_{11} & p_{21} & p_{31} \\ p_{12} & p_{22} & p_{32} \\ 1 - p_{11} - p_{12} & 1 - p_{21} - p_{22} & 1 - p_{31} - p_{32} \end{pmatrix}$$

We want to jointly estimate the parameters of the model conditional on being in a specific regime. The states are not observed, however it is possible to estimate the probability of being in one state based on current and past information. The full likelihood function of the model is given by a weighted average of the likelihood function in each state, where the weights are given by the state's probabilities. Hamilton's filter (Hamilton [1989, 1994]) provides an iterative procedure to estimate the unobserved filtered probabilities of each state based on the available information. Inference about s_t takes the form of a conditional probability $P(s_t = i | I_t, \theta)$. where $\theta = (\alpha_1, \alpha_2, \alpha_3, c_1, c_2, c_3, p_{11}, p_{22}, p_{21}, p_{31}, p_{12}, p_{32})$ is a vector of parameters to be estimated and $I_t = \{f_t^k, f_{t-1}^k, \dots, f_1^k\}$ denotes the set of observations as of date t .

We are interested in the filtered probability $P(s_t | I_t, \theta)$ of being in one state based on current and past information and the smoothed probability $P(s_t | I_T, \theta)$ of being in one state based on all the information available across the sample. Because they are based on more information, the smoothed probabilities provide a better information about the states at each period in time. The iterative procedure of Hamilton [1989] works as follows. Given the following normality assumption:

$$(y_t | s_t = i, I_{t-1}) \sim \mathcal{N}(\alpha_i + \beta_i f_{t-1}^k, \sigma_i^2)$$

Hence we know that the density of y_t conditional on I_{t-1} and $s_t = i$ is:

$$f(y_t | s_t = i, I_{t-1}; \theta) = \frac{1}{\sqrt{2\pi\sigma}} \exp \left[- \frac{(y_t - \alpha_i - \beta_i f_{t-1}^k)^2}{2\sigma_i^2} \right]$$

The algorithm to compute the density follows the following steps:

1. Computation of the joint probability $P(s_t, s_{t-1}|I_{t-1}; \theta)$ via Bayes theorem:

$$P(s_t = i, s_{t-1} = j|I_{t-1}; \theta) = P(s_t = i|s_{t-1} = j) \times P(s_{t-1} = j|I_{t-1})$$

This step can be initialized by setting $P(s_1 = j|I_1; \theta) = P(s_1 = j)$.

2. Computation of the probability $p(s_t|I_{t-1}; \theta)$:

$$p(s_t = i|I_{t-1}; \theta) = \sum_{j=1}^3 P(s_t = i, s_{t-1} = j|I_{t-1}, \theta)$$

3. Computing the joint density $f(y_t|s_t = j, I_{t-1}; \theta)$:

$$f(y_t|s_t = j, I_{t-1}; \theta) = \frac{1}{\sqrt{2\pi}\sigma_j} \exp\left[-\frac{(y_t - \alpha_j - \beta_j f_{t-1}^k)^2}{2\sigma_j^2}\right]$$

4. Computing the density of y_t conditional on I_{t-1} alone can be computed as:

$$f(y_t|I_{t-1}; \theta) = \sum_{j=1}^3 P(s_{t-1} = j|I_{t-1}; \theta) f(y_t|s_t = j, I_{t-1}; \theta)$$

5. Computing the filtered probability $P(s_t = i|I_t; \theta)$ with Bayes theorem:

$$P(s_t = i|I_t; \theta) = \frac{f(y_t, s_t = i|I_{t-1}; \theta)}{f(y_t|I_{t-1}; \theta)}$$

By iterating those step for $t = k, \dots, T$ and given the initial values $P(s_1 = i|I_0; \theta =)$, we obtain the filtering probabilities $P(s_t = i|I_t; \theta)$ as well as the conditional densities $f(y_t|I_{t-1}; \theta)$ for $t = 0, 1, \dots, T$. The likelihood of the whole process conditional on the first observation can be computed after T iterations of the filter algorithm by multiplying the conditional densities obtained at step 4:

$$f(y_T, y_{T-1}, \dots, y_2|y_1; \theta) = f(y_T|I_{T-1}; \theta) \times \dots \times f(y_3|I_2; \theta) \times f(y_2|I_1; \theta)$$

Eventually we get the log-likelihood:

$$\log f(y_1, y_2, \dots, y_T|x_0; \theta) = \sum_{t=1}^T \log f(y_t|I_{t-1}; \theta)$$

Once θ is estimated, we compute the smoothed probabilities $P(s_t|I_T; \theta)$ via the smoothing algorithm.

2.4.4 Results

The estimation suggests that allowing for switches in the mean, the coefficient of financial factors and the variance of the residuals is important to fit the data, which warrants the

modeling choice ex-post. Our model is able to identify recessions episodes for each financial factor. For each factor, we define the “financial stress regime” based on the correlation of the corresponding smoothed probabilities with recessionary episodes. To motivate the fact that the timing of our financial stress regimes is consistent with spikes in actual financial stress, we plot the smoothed probabilities of our so-called “financial stress regime” along with NBER recessions (Figure 2.9). As a robustness check, we also verify that “financial stress” smoothed probabilities correlate with the Kansas Fed Stress index, the Chicago Fed index and the Saint Louis Fed index.

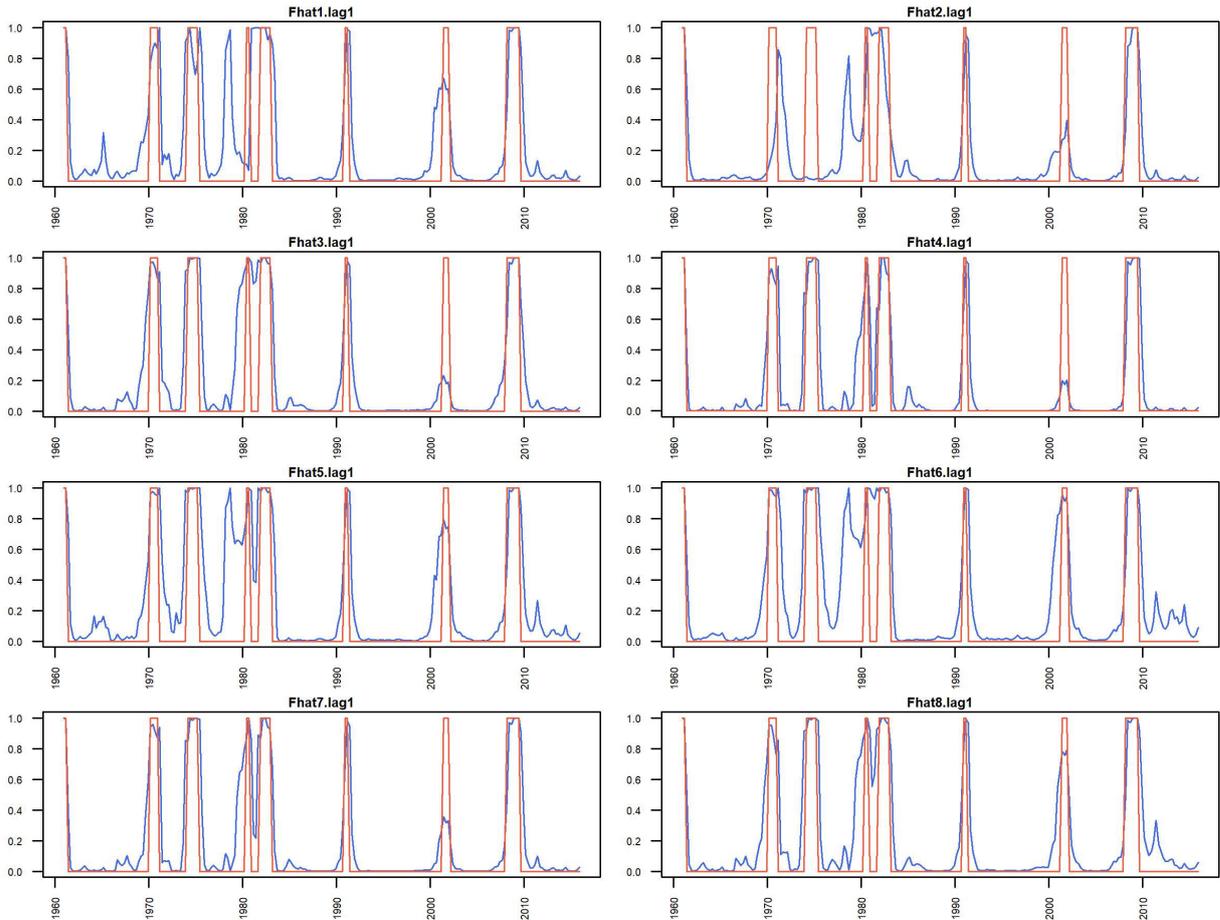


Figure 2.9: Smoothed probabilities corresponding to stress regimes and NBER recessions

Table 2.6 and Table 2.7 display the estimation output for factors 3 and 8. Factor 3 and 8 exhibit statistically significant relationship with output growth in the financial stress regime. The identification of factors 3 and 8 according to our decision rule is robust to the inclusion of time-varying probabilities as suggested by Diebold et al. [1994].

Table 2.6: Estimation output for \hat{f}_3

<i>Dependent variable: GDP</i>	
Regime 1	
\hat{f}_3	0.0021 (0.1894)
Constant	0.0073*** ($< 2e-16$)
Regime 2	
\hat{f}_3	-0.0018*** (0.7134)
Constant	0.0136*** (1.332e-15)
Financial stress regime	
\hat{f}_3	0.0088*** (0.00596)
Constant	0.0003 (0.88076)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2.7: Estimation output for \hat{f}_8

<i>Dependent variable: GDP</i>	
Regime 1	
\hat{f}_8	-0.0035 (0.2113)
Constant	0.0076*** ($< 2e-16$)
Regime 2	
\hat{f}_8	0.0060*** (0.5233)
Constant	0.0133*** ($< 2e-16$)
Financial stress regime	
\hat{f}_8	0.0125*** (0.009209)
Constant	0.0006 (0.764177)

Note: *p<0.1; **p<0.05; ***p<0.01

The transition probabilities for factor 3 yields:

	Regime 1	Regime 2	Stress regime
Regime 1	0.95992247	0.01309427	0.05428857
Regime 2	0.01292210	0.91131332	0.09031415
Stress regime	0.02715543	0.07559241	0.85539728

and the transition probabilities for factor 8 is:

	Regime 1	Regime 2	Stress Regime
Regime 1	0.95289135	0.01370682	0.0622907
Regime 2	0.01199501	0.90235942	0.1062713
Stress Regime	0.03511364	0.08393376	0.8314380

The transition probabilities show that the transition from a state of calm to a state of financial stress is rare, but once the economy is stuck in a stress episode, it takes some time to exit it. Moreover, as expected, the standard deviation of residuals in the stress regime is on average higher than in the two other regimes.

Turning to the economic interpretation of these results, the loadings help to give a sense of the forces captured by the two selected factors. Recall that factor 3 loads positively on stock prices, thereby potentially reflecting a combination of wealth, Tobin's Q and financial accelerator effects. Factor 8 is positively related to the term spread and potentially accounts for the empirical relationship between the slope of the yield curve and future economic conditions. Therefore, in addition to have a statistically significant impact on economic activity, the two factors exhibit coefficients in the stress regime that are consistent with the intuition

that a tightening of financial condition is negative for growth. Although they do not account for a large proportion of the overall variance in the financial dataset, the two factors are complementary as they embed variables from the bond market, the stock market and the exchange rate market. Therefore, they capture several channels of transmission of financial conditions to the real sector.

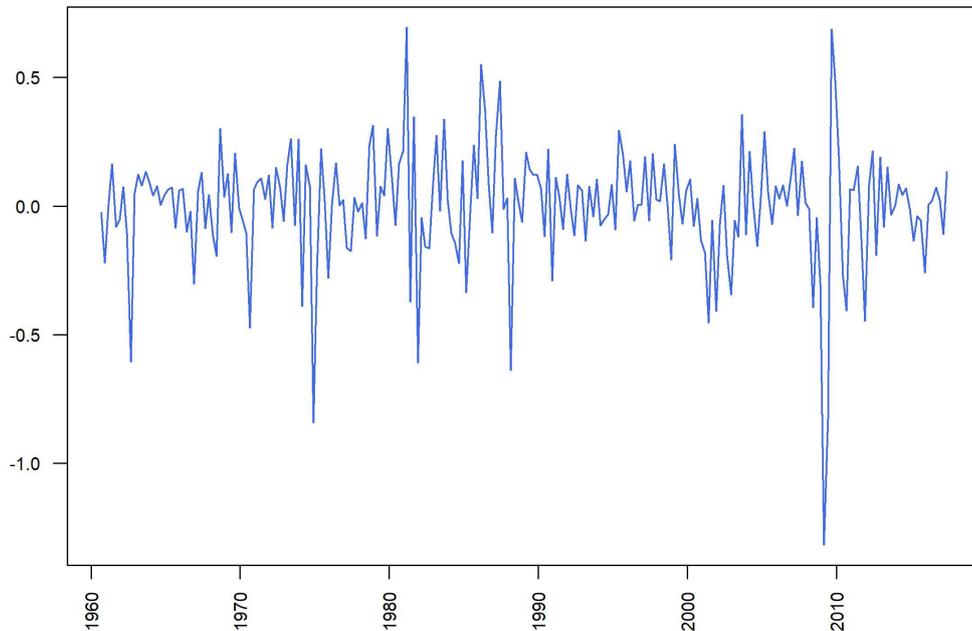


Figure 2.10: The Financial Condition Cycle

The Financial Condition Cycle is finally constructed as the sum of the two selected factors weighted by their respective percentage of variance explained (Figure 2.10). It is important to note that the aim of that section was not to build a new financial stress index, but instead to select the financial factors that affect adversely economic activity during financial stress episodes. Our analysis, however, comes with at least two caveats. First, our identification scheme is silent about the role of financial factors in the recession event. In particular, our findings do not indicate whether financial factors drive the recession in the first place, but only that conditional on being caught in a recession, they are aggravating factors. Second, our reduced-form model is obviously subject to the Lucas Critique, as it does not account for the two-way interaction between financial conditions and economic activity.

2.5 Are the Financial Cycle sub-components useful for the estimation of the output gap?

2.5.1 Introducing the output gap

By construction, the Credit Cycle and the Financial Condition Cycle interact with economic activity during financial crises or financial stress episodes respectively. Nothing guarantees however, that they are relevant for economic analysis. In this respect, we test in this section whether the two sub-components of the Financial Cycle convey information about the cyclical position of the economy, also known as the output gap. The output gap is indeed an input of paramount importance for the conduct of macroeconomic policy and its estimation is subject to potentially large measurement errors (Orphanides and Van Norden [2002]).

A non-zero output gap arises when the short run level of output departs from the long-run aggregate supply curve owing to temporary demand and supply shocks. In the case of a positive supply shock, higher productivity raises the return on capital and boosts investment. In the short-run, less labor is needed and real wages shrink. The disinflationary cycle stops when the new demand corresponding to the investment boost eventually arises. In the case of a positive demand shock, firms need more labor in the short-run to meet demand, which entails an increase in real wages and the cost of capital. Assuming a constant mark-up of prices over costs, this leads to higher prices and therefore a demand for higher wages. This inflationary loop between costs and prices continues as long as money supply follows money demand. When the central bank reacts to offset the demand shock and stabilize inflation, output returns to its steady state level. In either case, the output gap is associated with short-run disequilibrium in the labor market, an inflationary spiral and sub-optimal capacity utilization. In the long-run however, only a supply-side shock can have a permanent effect on the level of output that is compatible with a non-accelerating inflation rate. In this context, potential output is traditionally defined as “*the maximum production without inflation pressure*” (Okun [1962]). Recent works instead emphasize the concept of “sustainable” output and claim that other variables than the sole inflation should be used to gauge the state of the economy (Alberola et al. [2013]; Borio et al. [2014]).

Three main approaches can be used to estimate the output gap. The first is to use univariate statistical approaches. The first univariate method to decompose the trend and cycle component of output was proposed by the seminal work of Beveridge and Nelson [1981]. The authors define the permanent component of a time series y_t integrated of order 1 with a drift μ as the forecast at the infinite horizon, adjusted for the mean rate of growth. This definition entails that the trend of the time series at time t is a random walk, i.e. it is unpredictable based on previous information. If GDP growth is expected to be higher (lower) than average in the future, then GDP is below (above) trend. In contrast, the cyclical or transitory component consists in movements in the time series that can be forecast at all

horizons. Formally the trend T_t is defined by:

$$T_t = \lim_{k \rightarrow \infty} E_t \left[y_{t+k} - kE(\Delta y) \right] = y_t + \sum_{j=1}^{\infty} E_t \left[\Delta y_{t+j} - E(\Delta y) \right]$$

where $E_t[\cdot]$ denotes the expectation conditional on information available at time t . This method¹² however is seldom used nowadays because it yields estimates that are unconventional compared to other methods (Maravall [1993]).

The filtering methods of Hodrick and Prescott [1997], Baxter and King [1999] and Christiano and Fitzgerald [2003] bear upon spectral analysis in the frequency domain to decompose a time series into a trend component and a cycle component that fluctuates at a pre-determined frequency. The Hodrick and Prescott (HP) filter, that we will use as a benchmark in the rest of the section, for instance estimate potential output y_t^* by minimizing the following loss function:

$$\sum_{t=1}^T \left(\frac{1}{\sigma_1^2} (y_t - y_t^*)^2 + \frac{1}{\sigma_0^2} (\Delta y_{t+1}^* - \Delta y_t^*)^2 \right)$$

where σ_1^2 is the variance of the output gap and σ_0^2 is the variance of the change in potential output. The noise-to-signal ratio $\lambda = \sigma_1^2/\sigma_0^2$ determines the relative weight attached to deviations of potential output from actual output and to the smoothness of the potential output series itself¹³. A major drawback of the purely statistical approach, however, is the “end-point problem”, whereby estimates of the unobserved components are revised significantly when new data becomes available, which potentially entails a cost for economic policy in terms of efficiency (Orphanides and Van Norden [2002]). Berger et al. [2015] for example show that, in the run-up to the GFC, the HP-filter suggested level of potential output very close to actual output in euro area peripheral countries. Additionally, filtered series tend to reflect more the filter properties than the underlying data itself (King and Levine [1993]; Harvey and Jaeger [1993]; Boone [1995]).

A second method to isolate the cyclical component of output is to use Unobserved Component Time Series (UCTS) models (Harvey [1989]). UCTS models decompose output into different additive component each modeled by an appropriate dynamic stochastic process which usually depends on normally distributed disturbances. Consider, for instance, the local linear trend model, which breaks down output into a long-run component μ_t and a white noise transitory component ε_t :

$$\begin{aligned} y_t &= \mu_t + \varepsilon_t, & \text{with } \varepsilon_t \text{ i.i.d. } &\sim \mathcal{N}(0, \sigma_\varepsilon^2) \\ \mu_t &= \mu_{t-1} + \beta_{t-1} + \eta_t, & \text{with } \eta_t \text{ i.i.d. } &\sim \mathcal{N}(0, \sigma_\eta^2) \\ \beta_t &= \beta_{t-1} + \zeta_t, & \text{with } \zeta_t \text{ i.i.d. } &\sim \mathcal{N}(0, \sigma_\zeta^2) \end{aligned}$$

¹²In practice, the decomposition is obtained by fitting an ARMA(p,q) model to Δy_t and then computing the trend and cyclical component from the fitted model.

¹³Setting a strong relative penalty on potential growth is akin to fitting a straight line to actual output. On the contrary, imposing a strong relative penalty to deviations in potential output equalizes the trend and actual output.

This general form encompasses a wide range of possible specifications (see [Appendix](#)) such as a random walk with drift ($\sigma_\zeta^2 = 0$), an integrated random walk ($\sigma_\eta^2 = 0$) or a deterministic linear trend ($\sigma_\zeta^2 = \sigma_\eta^2 = 0$). The HP filter is a special case of the local linear trend model which fixes the ratio $\sigma_\zeta^2/\sigma_\varepsilon^2$. Instead of being modeled as a pure residual, the cycle ψ_t can be modeled as an autoregressive process:

$$\begin{aligned} y_t &= \mu_t + \psi_t + \varepsilon_t \\ \mu_t &= \mu_{t-1} + \beta_t + \eta_t \\ \beta_t &= \beta_{t-1} + \zeta_t \\ \psi_t &= \phi_1\psi_{t-1} + \phi_2\psi_{t-2} + \kappa_t \end{aligned}$$

where the roots of $1 - \phi_1 z - \phi_2 z^2 = 0$ are real and located outside the unit circle. Alternatively, the characteristic polynomial of ψ_t may have complex roots, such that:

$$\begin{cases} \psi_t = \rho \cos(\lambda)\psi_{t-1} + \rho \sin(\lambda)\psi_{t-1}^* + \kappa_t \\ \psi_t^* = \rho \cos(\lambda)\psi_{t-1}^* - \rho \sin(\lambda)\psi_{t-1} + \kappa_t^* \end{cases}$$

where λ is the frequency of the cyclical component, ρ is a persistence parameter restricted such as $0 \leq \rho \leq 1$ to ensure that the cycle is a stationary stochastic process.

The last approach to estimate the output gap bears upon partial equilibrium or structural models, via the production function approach or fully-fledged general equilibrium models. The production approach models the supply-side of the economy with a Cobb-Douglas function:

$$Y_t = A_t L_t^{1-\alpha} K_t^\alpha$$

where A is the total factor productivity (TFP), K is the level of the capital stock¹⁴ and L is the number of hours worked. α is the capital share to output growth. Potential output is the level of production when the three factors are at their potential levels. The potential level of hours worked depend on average weekly hours l , the natural rate of unemployment U^* and the potential labor force N^* , such that $L_t^* = l_t(1 - U_t^*)N_t^*$. TFP is defined as the residual when the two other factors are accounted for. A notable caveat of the production function approach however, is that it still requires to use statistical filters for detrending total factor productivity and employment.

A structural alternative to production function approach is to estimate New Keynesian Dynamic stochastic equilibrium (DSGE) models. In particular, for the estimation of the output gap, DSGE allow to distinguish between 1) “trend” output, which is the balanced-growth path arising solely from stochastic technology shocks, 2) “efficient” output, which would prevail if prices could adjust freely to changes in demand and supply and if the labour and goods markets were competitive (no mark-ups) and 3) “natural” output, arising from flexible prices and imperfect competition.

¹⁴Capital can be further decomposed into different categories such as computers and software, communications equipment, nonresidential structures, inventories and land.

The wide range of estimation techniques notwithstanding, the literature has converged on the necessity to include additional variables likely to correlate with the output gap. Seminal work in this respect includes [Cochrane \[1994\]](#), which bears upon the Permanent Income model¹⁵ to separate GNP into movements deemed permanent and transitory by consumers based on the departure of consumption from output.

The most common approach for the estimation of the output gap has been to use information contained in inflation and unemployment, on the premise that demand exceeding supply should lead to lower unemployment rate via Okun's law, and inflationary pressures via a Phillips curve (see for instance [Kuttner \[1994\]](#)). Model-based filters are UCTS models that offer a convenient and flexible way to do embed additional relationships to improve the estimation of unobserved components. Inflation may for instance be included via the following generic model:

$$\begin{bmatrix} y_t \\ \pi_t \end{bmatrix} = \begin{bmatrix} \mu_t^y \\ \mu_t^\pi \end{bmatrix} + \begin{bmatrix} \psi_t^y \\ \psi_t^\pi \end{bmatrix} + \begin{bmatrix} \varepsilon_t^y \\ \varepsilon_t^\pi \end{bmatrix}$$

The trends are unit roots with drift:

$$\begin{bmatrix} \mu_t^y \\ \mu_t^\pi \end{bmatrix} = \begin{bmatrix} \beta_t^y \\ \beta_t^\pi \end{bmatrix} + \begin{bmatrix} \mu_{t-1}^y \\ \mu_{t-1}^\pi \end{bmatrix} + \begin{bmatrix} \eta_t^y \\ \eta_t^\pi \end{bmatrix}$$

The cycle component $\Psi_t = [\psi_t^y \ \psi_t^\pi]'$ follows a VAR process:

$$\Psi_t = A(L)\Psi_{t-1} + v_t$$

The covariance matrix Ω of the trend and cycle law of motions is block diagonal and governs the link between output and inflation and their components, thereby adding a contemporaneous link between inflation and the output gap through their unpredictable elements:

$$\Omega = \begin{bmatrix} \omega_{yy}^\mu & \omega_{y\pi}^\mu & 0 & 0 \\ \omega_{y\pi}^\mu & \omega_{\pi\pi}^\mu & 0 & 0 \\ 0 & 0 & \omega_{yy}^\Psi & \omega_{y\pi}^\Psi \\ 0 & 0 & \omega_{y\pi}^\Psi & \omega_{\pi\pi}^\Psi \end{bmatrix}$$

Alternatively, the additional observable variable can be restricted to interact solely with the cyclical component of output. [Clark \[1989\]](#) for instance include unemployment (u_t) as a lagging indicator of the Business Cycle:

¹⁵The Permanent Income model predicts that consumption is a random walk and that consumption and total income are cointegrated.

$$\begin{aligned}
y_t &= \mu_t^y + \psi_t \\
\mu_t^y &= \mu_{t-1}^y + \beta + \eta_t^y \\
\psi_t &= \phi_1 \psi_{t-1} + \phi_2 \psi_{t-2} + \kappa_t \\
u_t &= \mu_t^u + \theta_1 \psi_t + \theta_2 \psi_{t-1} \\
\mu_t^u &= \mu_{t-1}^u + \eta_t^u
\end{aligned}$$

Adding additional variables to pin down the output gap additionally solves a source of indeterminacy inherent to univariate UCTS models. The output of univariate UCTS models indeed tend to hinge crucially on the assumption made about the correlation between the trend residual (η_t) and the cycle residual (κ_t). When the correlation is forced to be zero, as in Clark [1987], or estimated to be zero as in Clark [1989], the resulting estimates of the cycle are conventional. By contrast, with a non-zero correlation, the trend component captures the bulk of GDP variability and the cycle is mere noise and cannot be used as a measure of the output gap (Nelson and Plosser [1982] and Morley et al. [2003]). Moreover, Basistha [2007] uses a Monte Carlo simulation to show that univariate filters may estimate the trend-cycle correlation to be non-zero even when it is zero in the data generating process. On the contrary, multivariate models can estimate the true underlying correlation between the cycle and the trend component. Clark [1989] show that in that case, the innovations in the trend and cyclical components are estimated to be independent without further restrictions.

Although the inclusion of variables such as inflation, unemployment or capacity utilization has proved to be helpful for the estimation of the output gap, recent research suggests that the information content of inflation for potential output has decreased over recent periods (Borio et al. [2014]). First, inflation expectations became more anchored, and thereby less volatile, with the “Great Moderation”. Second, in an open-economy context, inflation dynamics are increasingly synchronized with global factors. Increasing global supply and stronger competition owing to the international integration of product markets, like China joining the World Trade Organization, alongside with technological progress, imposed downward pressure on consumer prices. Additionally, while excess demand creates excess employment and inflation via the non-tradeable sector, the trade balance absorbs the excess demand in the tradeable sector and may not materialize in changes in inflation (Darvas and Simon [2015]). Additionally, the GFC compels us to rethink the concept of “potential” output, in favor of “sustainable” output. Imbalances such as housing bubbles or excessive credit expansions have proven to be highly destabilizing in the long-run, without necessarily materializing into higher consumer inflation. Borio et al. [2016] explain that a financial boom may not necessarily lead to consumer price inflation if among other things, it relaxes supply-side constraints, it is followed by capital inflows that entail currency appreciation and lower imported inflation, or it materializes in cross-sector misallocation rather than aggregate capacity constraints. As a result, output growth can be unsustainable even under low and stable inflation. Consequently, the inclusion of financial information may improve the estimation of the output gap (Borio et al. [2014]). In a DSGE model with financial frictions, Furlanetto et al. [2014] show that

the discrepancy between actual and potential output associated solely to financial frictions is strongly correlated with the default risk spread, which suggests that financial factors can be helpful for the estimation of the output gap. In the rest of the section, we use a model-based UCTS model to study whether the two sub-components of the Financial Cycle embed valuable information for the estimation of the output gap. Model-based filters have been used to study the interaction between the Business Cycle and the Financial Cycle in a number of studies, including [Koopman and Lucas \[2005\]](#), [Galati et al. \[2016\]](#) and [Rünstler and Vlekke \[2018\]](#).

2.5.2 The model

Our model starts from the HP-filter in state-space form. The state equation describes the law of motion of the growth rate of potential output y_t^* , which follows a random walk:

$$\Delta y_{t+1}^* = \Delta y_t^* + v_{t+1}, \text{ with } v_t \sim \mathcal{N}(0, \sigma_v^2)$$

The measurement equation relates potential output to actual output y_t :

$$y_t = y_t^* + u_t, \text{ with } u_t \sim (0, \sigma_u^2)$$

where u_t and v_t are assumed to be uncorrelated at all lags and leads.

A major drawback of this specification, however, is that the output gap is assumed to be a white noise process, while we would expect it to exhibit autocorrelation. We therefore augment the measurement equation with a lagged output gap component:

$$y_t = y_t^* + \beta(y_{t-1} - y_{t-1}^*) + u_t$$

Additionally, we augment the measurement equation with the components of the Financial Cycle computed earlier. [Borio et al. \[2014\]](#) show that a robust way of embedding economic information in output gap estimates is to augment the measurement equation with additional variables x_t as follows:

$$y_t = y_t^* + \alpha' x_t + \beta(y_{t-1} - y_{t-1}^*) + u_t$$

The new measurement equation is akin to an extended IS-curve, where measures of the Financial Cycle are used instead of the real interest rate. As explained by [Borio et al. \[2014\]](#), the advantage of that specification is that the output gap is not forced to explain x_t as in classic multivariate filters. Indeed, only variables that are directly relevant in explaining the output gap beyond its autoregressive component will receive a non-zero α parameter. This approach therefore lessens the impact of potential misspecifications. Importantly, with that specification financial factors are assumed to affect only the cyclical component of output. In practice, especially in the presence of a banking crisis, it is highly possible that financial factors also affect potential output itself.

One consequence of augmenting the measurement equation is that u_t is no longer the

cycle component. To ensure that the volatility of the estimated output gap is in line with standard estimates, we follow [Borio et al. \[2014\]](#). We start with a low signal-to-noise ratio σ_u^2/σ_v^2 and increase it iteratively until the following equality holds:

$$\text{Var}(y_t - y_{\text{HP},t}^*)/\text{Var}(y_{\text{HP},t}^* - y_{\text{HP},t-1}^*) = \text{Var}(y_t - y_t^*)/\text{Var}(y_t^* - y_{t-1}^*)$$

where $y_{\text{HP},t}^*$ and y_t^* are potential output estimated by the static HP filter and the augmented dynamic filter respectively.

In matrix form, the measurement equation of the final model becomes:

$$y_t = \begin{bmatrix} 1 + \beta & -\beta \end{bmatrix} \begin{bmatrix} y_t^* \\ y_{t-1}^* \end{bmatrix} + Ax_t + v_t$$

and the transition equation is:

$$\begin{bmatrix} y_t^* \\ y_{t-1}^* \end{bmatrix} = \begin{bmatrix} 2 & -1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} y_{t-1}^* \\ y_{t-2}^* \end{bmatrix} + \begin{bmatrix} u_t \\ 0 \end{bmatrix}$$

$$Q = \begin{bmatrix} \sigma_v^2 & 0 \\ 0 & 0 \end{bmatrix} \quad \text{and} \quad R = \text{E}[u_t u_t'] = \sigma_u^2$$

The linear least square estimate of the state vector $s_t = [y_t^* \ y_{t-1}^*]'$, can be estimated recursively with the Kalman filter. For the sake of simplicity, we use standard notations and consider the general state-space model with N observables, K latent variables and M predetermined variables:

$$\begin{cases} y_t = Ax_t + Bs_t + u_t, & \text{with } u_t \sim \mathcal{N}(0, R) \\ s_t = \Phi s_{t-1} + v_t, & \text{with } v_t \sim \mathcal{N}(0, Q) \end{cases}$$

where u_t and v_t are independent at all leads and lags. A is $M \times 1$, B is $N \times K$, Φ is $K \times K$, $R = \text{E}[u_t u_t']$ is $N \times N$ and $Q = \text{E}[v_t v_t']$ is $K \times K$.

We define $a_{t|t-1} = \text{E}[s_t | I_{t-1}]$ and $P_{t|t-1} = \text{Cov}(s_t | I_{t-1})$. The Kalman filter ([Kalman \[1960\]](#); [Kalman and Bucy \[1961\]](#)) is the optimal linear filter for generating mean square error forecasts in a state-space model and solving for the expected value of the unobserved state variables conditional on observables. More precisely, the algorithm computes recursively estimates of $a_{t|t}$ and $P_{t|t}$ which fully pins down the conditional density of the state variable (see the [Appendix](#) for a proof of the Kalman Filter recursions).

We define the conditional mean of y_t based on information at time $t-1$, $y_{t|t-1} = E_{t-1}[y_t]$, with variance $V_{t|t-1} = E[(y_t - y_{t|t-1})^2]$. The best estimator of the state variable s_t based on information at time $t-1$ is the conditional mean $s_{t|t-1} = E[s_t | I_{t-1}] = E_{t-1}[s_t]$, with variance $P_{t|t-1} = E[(s_t - s_{t|t-1})^2]$. Assuming that the initial state vector $s_0 \sim \mathcal{N}(\mu_0, \Sigma_0)$ and given μ_0 and Σ_0 , the Kalman filter consists in a sequence of iterative prediction and update steps. The first step consists of computing the best *ex ante* estimate of the state vector thanks to

the transition equation:

$$\begin{cases} s_{t|t-1} = \Phi s_{t-1|t-1} \\ P_{t|t-1} = \Phi P_{t-1|t-1} \Phi' + Q \end{cases}$$

$s_{t|t-1}$ is then used to compute the prediction error of the measurement equation relative to the actual value of y_t :

$$\begin{cases} y_{t|t-1} = B s_{t|t-1} \\ V_{t|t-1} = B P_{t|t-1} B' + R \end{cases}$$

The last step consists in updating the state vector by allowing part of the prediction error to feed through. When new information on the observable y_t becomes available, a better estimator of s_t is given by the updated conditional mean $s_{t|t} = E_t[s_t]$ with variance $P_{t|t} = E[(s_t - s_{t|t})^2]$. The current estimation of $s_{t|t}$ is the weighted sum of $s_{t|t-1}$ (its predicted value at time $t - 1$), and of the prediction error based on the last value of the observable variables $y_t - y_{t|t-1}$:

$$\begin{cases} s_{t|t} = s_{t|t-1} + K_t(y_t - y_{t|t-1}) \\ P_{t|t} = P_{t|t-1} - K_t B P_{t|t-1} \end{cases}$$

where $K_t = P_{t|t-1} B' V_{t|t-1}^{-1}$ is called the Kalman Gain. The bigger the variance of the measurement error, the lower the weight given to the information carried by the measurement equation in making the forecast for the next period given today's information set and the lower the Kalman gain.

Unknown model parameters can be estimated using standard maximum likelihood and the Kalman filter. The Kalman filter is therefore used both for the estimation of parameters and for the computation of the state variables. Parameters α , β and σ_2 are estimated using a Bayesian procedure, which allows to pass from a prior to a posterior distribution of the parameters in light of data. Our objective is to characterize the joint posterior distribution of potential output, output gap and of the parameters conditionally on the data, i.e. $P(y^*, \theta | I_T)$, where $I_T = \{y_1, \dots, y_T; x_1, \dots, x_T\}$. Bayes's law allows to obtain draws from $P(y^*, \theta | I_T)$ by using prior information on the parameter θ :

$$P(\theta | I_T) \propto \mathcal{L}(I_T; \theta) \pi(\theta)$$

where $\mathcal{L}(I_T; \theta)$ is the likelihood of data $I_t = \{y_1, \dots, y_T; x_1, \dots, x_T\}$ evaluated at the vector of parameters θ and $\pi(\theta)$ is the prior density. The Kalman filter allows the computation of the log-likelihood of the system $\mathcal{L}(I_T; \theta)$ and therefore allows to draw samples from the posterior distribution of parameters conditional on the full dataset I_T using Markov Chain Monte Carlo techniques.

We impose that the priors for α , β and σ_2 follow a gamma distribution with a prior mean 0.7 for α and β and 1 for σ_2 and a common standard deviation of 1 for the three parameters. β are required to be positive to ensure consistency and lower than 0.95 to avoid unit roots. Because we restrict our analysis to the positive short to medium-term effects of financial factors on the cyclical movements in output, we impose that α is positive. Consequently, the model does not directly account for the long-run adverse effect of financial factors on

growth¹⁶. Posterior draws which do not meet these assumptions are discarded. Once α , β and σ_2 are estimated (σ_0 is directly pinned down by σ_2), the state vector can be extracted from the observations using the Kalman filter and the associated smoother¹⁷ of Durbin and Koopman [2012].

2.5.3 Results

We estimate the model individually with the Credit Cycle and the Financial Condition Cycle. For the two models, α and β are found to be non-zero, thereby confirming first that the output gap exhibits significant persistence and that financial factors convey information about the cyclical movements in output. For the model that incorporates the Credit Cycle, the posterior distributions of the model parameters are shown in Figure 2.11. Figure 2.12 illustrates that the inclusion of the Credit Cycle in the estimation of the output gap helps to detect potential unsustainable growth patterns. In particular, the model signals that in the years preceding the GFC, actual output departed much more from its potential than what a simple HP filter would suggest. By the same token, the model indicates more excess capacity during the Great Recession. Therefore, the Credit Cycle seems to embed valuable information about the output gap around turning points, where the cost of an inappropriate policy mix is higher.

As shown by Figure 2.13, α is estimated to be close to zero in the model that includes the Financial Condition Cycle. Therefore, unlike the Credit Cycle, the inclusion of the Financial Condition Cycle does not affect the decomposition provided by the HP filter (Figure 2.14). This should not come as a surprise, as it has been constructed from differentiated times series, thereby omitting potential stock effects that could reflect unstable funding scheme. Moreover, this is consistent with the fact that estimating the unconditional impact of financial conditions on economic activity is fraught with pitfalls, which was the reason why we focused on non-linear feedbacks effects in the previous section. As we will see, this does not mean, however, that the Financial Condition Cycle is irrelevant to the estimation of the output gap.

¹⁶Modeling the intertemporal trade-off between short-term growth and the likelihood of financial crises is relatively complex and would require a non-linear model, which is beyond the scope of this analysis.

¹⁷The Kalman smoother is a backward recursion which computes the mean and variance of the state vector based on the full data set.

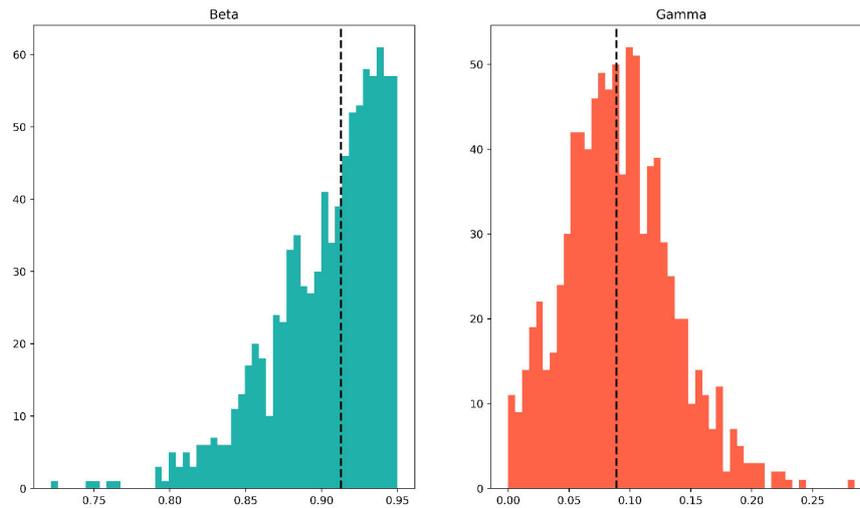


Figure 2.11: Posterior draws (post burn-in) for the Credit Cycle



Figure 2.12: Output gap for the Credit Cycle

Turning to the real-time estimation of the output gap, we test whether the inclusion of two sub-components of the Financial Cycle improves upon the static HP-filter for the real-time estimation of the output gap. So far, we have estimated potential output via the Kalman smoother, which uses the full information set, not available to the policymaker in real-time. The ex-post estimation of the output gap is interesting *per se*, but provides little guidance for the conduct of fiscal or monetary policy as the full-sample estimates of the output gap will most likely differ from the real-time estimate. For the two models, we compute the mean-squared error between the full-sample and the real-time estimates. We find that the mean-squared errors of the models that include the Credit Cycle and the Financial Condition

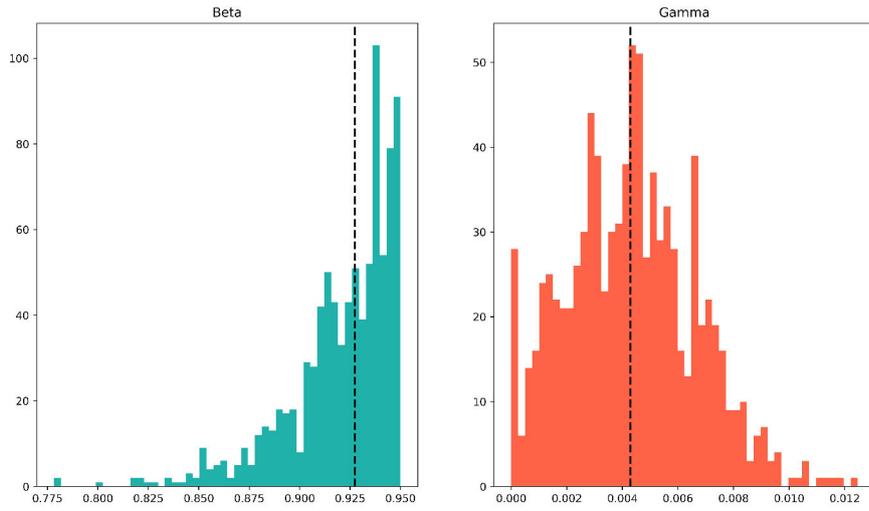


Figure 2.13: Posterior draws (post burn-in) for the Financial Condition Cycle

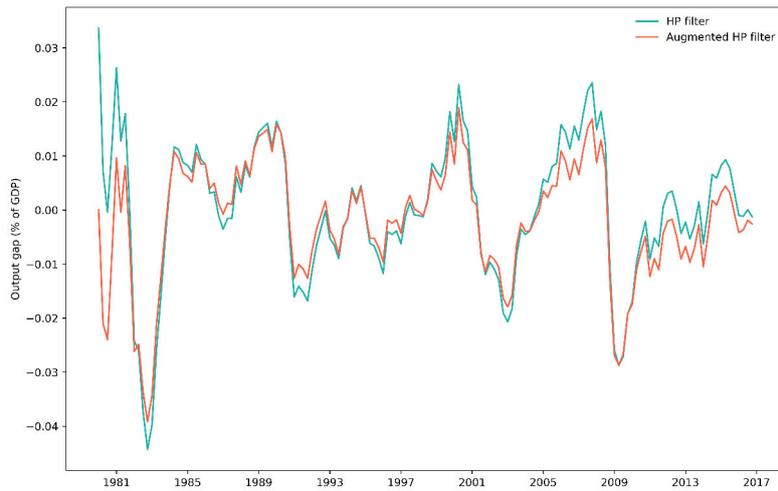
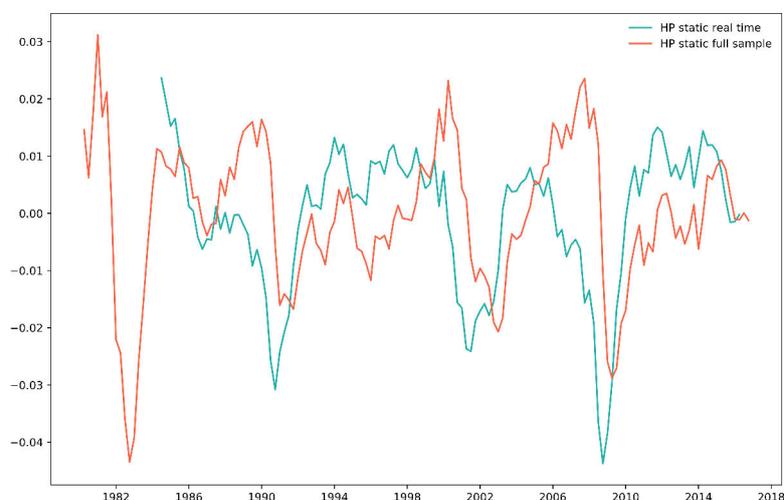


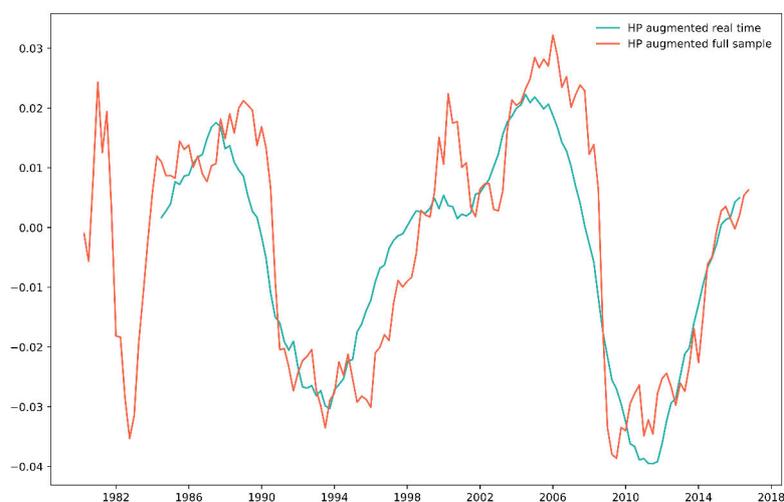
Figure 2.14: Output gap with the Financial Condition Cycle

Cycle ($7.981e^{-5}$ and $8.061e^{-5}$, respectively) are three times lower than the mean squared error of the HP filter with no covariates ($21.641e^{-5}$). [Figure 2.15 \(a\)](#) and [Figure 2.15 \(b\)](#) show the real time estimate and full sample estimates for the static HP filter and the Credit Cycle model. Our two measures of the Financial Cycle, although they contribute differently to the estimation of the output gap, are therefore helpful for the estimation of the output gap in real-time and may improve the policy prescriptions accordingly.

Figure 2.15: Full sample vs Real time output gap



(a) Static HP filter



(b) Credit Cycle augmented filter

2.6 Conclusion

In this chapter, we highlighted strong correlations between financial factors and economic activity by decomposing the Financial Cycle into two different components. Our identification procedure bore upon specific events where macro-financial linkages are reinforced. Considering two different Financial Cycles made it possible to investigate the dichotomy between the short and long-term consequences of financial factors. An assessment of the degree of interplay between the Credit Cycle and the Financial Condition Cycle represents another avenue for research. Interesting work in this area includes for instance [Adrian et al. \[2018\]](#), which

show that adding rapid credit growth to loose financial conditions dampens even further the first percentile of growth in the medium term. A major caveat of that chapter, however, is that it does not allow to draw conclusion about the causal relationship between financial and economic factors. In the next chapter, we specify a structural model that makes it possible to study the causal impact of financial shocks on economic activity.

Appendix A

Chapter 2 - Appendix

A.1 Different specifications for the simple UCTS model

Table A.1: Different specifications of the Unobserved Component Time Series Model

	σ_ε	σ_η	σ_ζ
Deterministic trend	*	0	0
Level with fixed slope	*	*	0
Random walk with fixed drift	0	*	0
Local linear trend	*	*	*
Smooth trend	*	0	*

A.2 The Kalman Filter

A.2.1 Proof of the Kalman Filter Recursions

This section presents the proof of the Kalman filter provided by [Meinhold and Singpurwalla \[1983\]](#). Consider a state-space model with N observables, K latent variables and M predetermined variables as follows:

$$\begin{cases} y_t = Ax_t + Bs_t + u_t, & \text{with } u_t \sim \mathcal{N}(0, R) \\ s_t = \Phi s_{t-1} + v_t, & \text{with } v_t \sim \mathcal{N}(0, Q) \end{cases}$$

We use the following properties of multivariate normal distributions:

1.

$$y \sim \mathcal{N}(\mu_y, \Sigma_y), z \sim \mathcal{N}(\mu_z, \Sigma_z), \text{ with } y \perp z \Rightarrow y + z \sim \mathcal{N}(\mu_y + \mu_z, \Sigma_y + \Sigma_z)$$

2.

$$Ay + c \sim \mathcal{N}(A\mu_y, A\Sigma_y A')$$

3.

$$\begin{bmatrix} z \\ y \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \mu_z \\ \mu_y \end{bmatrix}, \begin{bmatrix} \Sigma_z & \Sigma_{zy} \\ \Sigma_{yz} & \Sigma_y \end{bmatrix}\right)$$

$$z|y \sim \mathcal{N}(\mu_z + \sigma_{zy}\Sigma_y^{-1}(y - \mu_y), \Sigma_z - \Sigma_{zy}\Sigma_y^{-1}\Sigma_{yz})$$

Prediction and correction steps for $t = 1$:

$$\begin{aligned} \begin{bmatrix} s_1 \\ y_1 \end{bmatrix} &= \begin{bmatrix} I \\ B \end{bmatrix} s_0 + \begin{bmatrix} 0 \\ Gx_1 \end{bmatrix} + \begin{bmatrix} 0 \\ I \end{bmatrix} u_1 \\ &= \begin{bmatrix} I \\ B \end{bmatrix} \Phi s_0 + \begin{bmatrix} 0 \\ Gx_1 \end{bmatrix} + \begin{bmatrix} I & 0 \\ B & I \end{bmatrix} \begin{bmatrix} v_0 \\ u_1 \end{bmatrix} \end{aligned}$$

Therefore:

$$\begin{bmatrix} s_1 \\ y_1 \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \Phi\mu_0 \\ B\Phi\mu_0 \end{bmatrix}, \begin{bmatrix} I & 0 \\ B & I \end{bmatrix} \begin{bmatrix} \Sigma_v & 0 \\ 0 & \Sigma_u \end{bmatrix} \begin{bmatrix} I & B' \\ 0 & I \end{bmatrix} + \begin{bmatrix} \Phi \\ B\Phi \end{bmatrix} \Sigma_0 \Phi' B'\right)$$

As a result, the prediction step for $t = 1$ is:

$$\begin{aligned} s_{1|0} &= \mathbb{E}(s_1) = \Phi\mu_0 = \Phi s_{0|0} \\ \Sigma_s(1|0) &= P_{1|0} = \text{Cov}(s_1) = \Phi\Sigma_0\Phi' + \Sigma_v = \Phi\Sigma_s(0|0)\Phi' + \Sigma_v \\ y_{1|0} &= \mathbb{E}(y_1) = Bz_{1|0} \\ \Sigma_y(1|0) &= V_{1|0} = \text{Cov}(y_1) = B\Sigma_v B' + \Sigma_u + B\Phi\Sigma_0\Phi'B' = B\Sigma_s(1|0)B' + \Sigma_u \end{aligned}$$

The conditional distribution of s_1 given y_1 gives the correction step for $t = 1$:

$$s_1|y_1 \sim \mathcal{N}\left(s_{1|0} + P_{1|0}B'V_{1|0}^{-1}(y_1 - y_{1|0}), V_{1|0} - V_{1|0}BP_{1|0}^{-1}BV_{1|0}\right)$$

The prediction step can be generalized under the normality assumption:

$$(s_t|y_1, \dots, y_{t-1}) \sim \mathcal{N}(s_{t|t-1}, P_{t|t-1}), \quad t = 2, \dots, T$$

$$(s_t|y_1, \dots, y_t) \sim \mathcal{N}(s_{t|t}, P_{t|t}), \quad t = 1, \dots, T$$

$$(y_t|y_1, \dots, y_{t-1}) \sim \mathcal{N}(y_{t|t-1}, V_{t|t-1}), \quad t = 1, \dots, T$$

A.2.2 Maximum Likelihood Estimation of State Space Models

So far we have assumed that the population parameters $\theta = \{A, B, \Phi, R, Q\}$ were known. In practice it is necessary to estimate these parameters. Since s_t is unobservable, we cannot estimate the parameters by simple regression. By Bayes' theorem, the sample density function can be written:

$$\begin{aligned}
f(y_1, \dots, y_T; \theta) &= f(y_1; \theta) f(y_2, \dots, y_T | y_1; \theta) \\
&\vdots \\
&= f(y_1; \theta) f(y_2 | y_1; \theta) \dots f(y_T | y_1, \dots, y_{T-1}; \theta)
\end{aligned}$$

$$\begin{aligned}
\ln \mathcal{L}(\theta | y_1, \dots, y_T) &= \ln f(y_1, \dots, y_T; \theta) \\
&= \ln f(y_1; \theta) + \sum_{t=2}^T \ln f(y_t | y_1, \dots, y_{t-1}; \theta) \\
&= -\frac{T}{2} \ln(2\pi) - \frac{1}{2} \sum_{t=1}^T \ln |V_{t|t-1}| - \frac{1}{2} \sum_{t=1}^T (y_t - y_{t|t-1})' V_{t|t-1}^{-1} (y_t - y_{t|t-1})
\end{aligned}$$

because

$$(y_t | y_1, \dots, y_{t-1}) \sim \mathcal{N}(y_{t|t-1}, V_{t|t-1}), \quad t = 1, \dots, T$$

The log-likelihood function for the entire sample is a nonlinear function of θ via $y_{t|t-1}$ and $V_{t|t-1}$ which depend on θ . For a given θ , the likelihood can be computed through the Kalman filter recursions.

A.3 Concordance analysis

Table A.2: Concordance table (1/3)

US						
	gdp	property	credit.to.gdp	credit	equity	exchange.rate
gdp	1	0.722	0.736	0.889	0.743	0.569
property		1	0.75	0.708	0.604	0.639
credit.to.gdp			1	0.833	0.562	0.514
credit				1	0.688	0.556
equity					1	0.59
exchange.rate						1

UK						
	gdp	property	credit.to.gdp	credit	equity	exchange.rate
gdp	1	0.75	0.701	0.875	0.701	0.424
property		1	0.688	0.792	0.66	0.465
credit.to.gdp			1	0.826	0.528	0.528
credit				1	0.688	0.438
equity					1	0.528
exchange.rate						1

Finland						
	gdp	property	credit.to.gdp	credit	equity	exchange.rate
gdp	1	0.715	0.535	0.66	0.66	0.41
property		1	0.569	0.583	0.75	0.514
credit.to.gdp			1	0.861	0.5	0.528
credit				1	0.556	0.528
equity					1	0.514
exchange.rate						1

Japan						
	gdp	property	credit.to.gdp	credit	equity	exchange.rate
gdp	1	0.5	0.562	0.771	0.618	0.424
property		1	0.715	0.646	0.618	0.521
credit.to.gdp			1	0.694	0.528	0.319
credit				1	0.653	0.472
equity					1	0.486
exchange.rate						1

Germany						
	gdp	property	credit.to.gdp	credit	equity	exchange.rate
gdp	1	0.465	0.528	0.764	0.681	0.472
property		1	0.424	0.521	0.507	0.438
credit.to.gdp			1	0.708	0.528	0.597
credit				1	0.653	0.583
equity					1	0.583
exchange.rate						1

New-Zealand						
	gdp	property	credit.to.gdp	credit	equity	exchange.rate
gdp	1	0.75	0.653	0.819	0.583	0.451
property		1	0.611	0.653	0.625	0.326
credit.to.gdp			1	0.833	0.486	0.465
credit				1	0.542	0.521
equity					1	0.368
exchange.rate						1

Table A.3: Concordance table (2/3)

Belgium						
	gdp	property	credit.to.gdp	credit	equity	exchange.rate
gdp	1	0.715	0.583	0.653	0.694	0.479
property		1	0.646	0.701	0.576	0.319
credit.to.gdp			1	0.917	0.569	0.479
credit				1	0.597	0.465
equity					1	0.562
exchange.rate						1

Canada						
	gdp	property	credit.to.gdp	credit	equity	exchange.rate
gdp	1	0.715	0.653	0.854	0.694	0.451
property		1	0.632	0.722	0.604	0.431
credit.to.gdp			1	0.799	0.514	0.493
credit				1	0.618	0.486
equity					1	0.451
exchange.rate						1

Netherlands						
	gdp	property	credit.to.gdp	credit	equity	exchange.rate
gdp	1	0.826	0.639	0.792	0.75	0.41
property		1	0.562	0.646	0.632	0.458
credit.to.gdp			1	0.819	0.542	0.549
credit				1	0.639	0.493
equity					1	0.618
exchange.rate						1

France						
	gdp	property	credit.to.gdp	credit	equity	exchange.rate
gdp	1	0.688	0.66	0.875	0.708	0.472
property		1	0.583	0.646	0.507	0.382
credit.to.gdp			1	0.785	0.562	0.493
credit				1	0.694	0.458
equity					1	0.542
exchange.rate						1

Italy						
	gdp	property	credit.to.gdp	credit	equity	exchange.rate
gdp	1	0.521	0.521	0.583	0.597	0.465
property		1	0.639	0.729	0.438	0.361
credit.to.gdp			1	0.799	0.451	0.486
credit				1	0.542	0.535
equity					1	0.507
exchange.rate						1

Ireland						
	gdp	property	credit.to.gdp	credit	equity	exchange.rate
gdp	1	0.708	0.597	0.812	0.66	0.472
property		1	0.556	0.562	0.688	0.444
credit.to.gdp			1	0.785	0.521	0.458
credit				1	0.583	0.424
equity					1	0.465
exchange.rate						1

Table A.4: Concordance table (3/3)

Denmark						
	gdp	property	credit.to.gdp	credit	equity	exchange.rate
gdp	1	0.701	0.528	0.736	0.66	0.5
property		1	0.59	0.674	0.653	0.549
credit.to.gdp			1	0.792	0.521	0.528
credit				1	0.576	0.472
equity					1	0.618
exchange.rate						1

Sweden						
	gdp	property	credit.to.gdp	credit	equity	exchange.rate
gdp	1	0.736	0.632	0.826	0.701	0.472
property		1	0.576	0.715	0.674	0.486
credit.to.gdp			1	0.792	0.514	0.549
credit				1	0.597	0.549
equity					1	0.507
exchange.rate						1

Spain						
	gdp	property	credit.to.gdp	credit	equity	exchange.rate
gdp	1	0.764	0.611	0.701	0.556	0.431
property		1	0.569	0.66	0.528	0.431
credit.to.gdp			1	0.854	0.472	0.5
credit				1	0.549	0.479
equity					1	0.528
exchange.rate						1

Norway						
	gdp	property	credit.to.gdp	credit	equity	exchange.rate
gdp	1	0.708	0.507	0.708	0.625	0.562
property		1	0.549	0.639	0.681	0.479
credit.to.gdp			1	0.729	0.479	0.556
credit				1	0.625	0.59
equity					1	0.507
exchange.rate						1

Switzerland						
	gdp	property	credit.to.gdp	credit	equity	exchange.rate
gdp	1	0.694	0.604	0.764	0.701	0.465
property		1	0.59	0.681	0.521	0.438
credit.to.gdp			1	0.799	0.639	0.528
credit				1	0.688	0.479
equity					1	0.528
exchange.rate						1

A.4 Turning points analysis

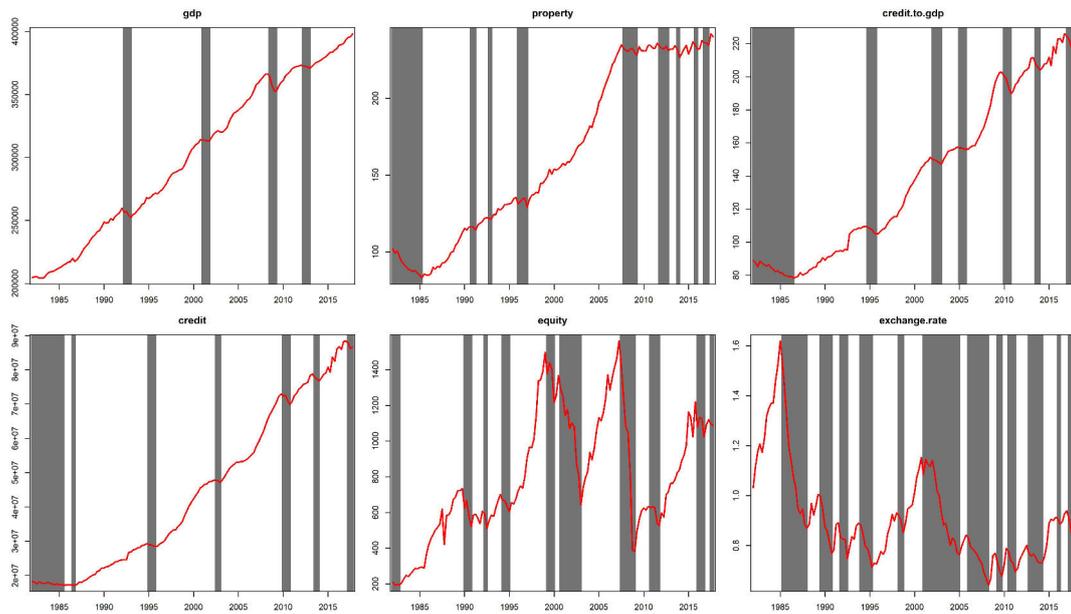


Figure A.1: Belgium

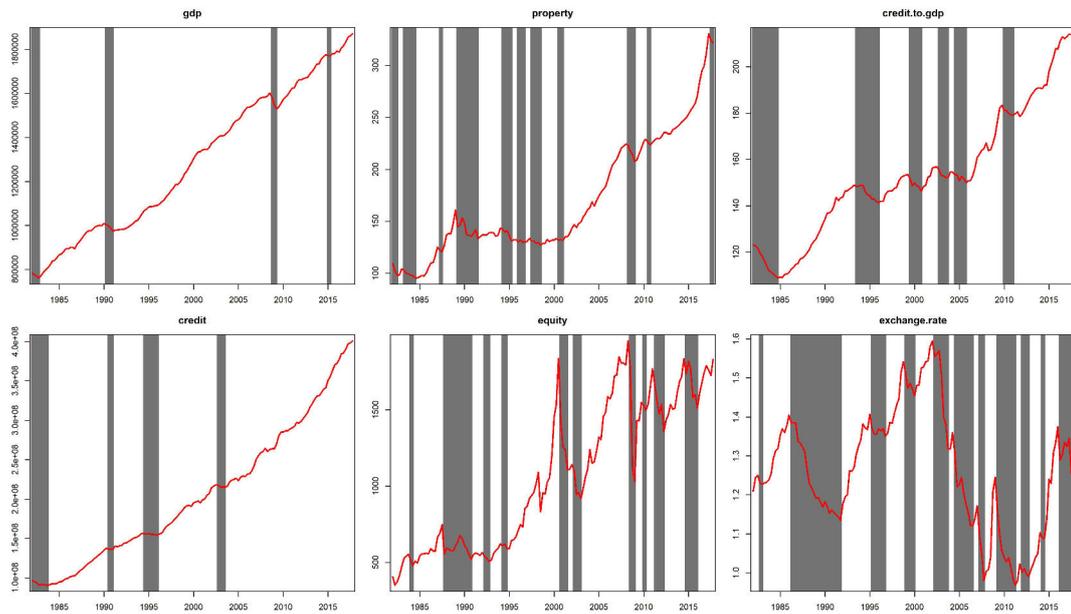


Figure A.2: Canada

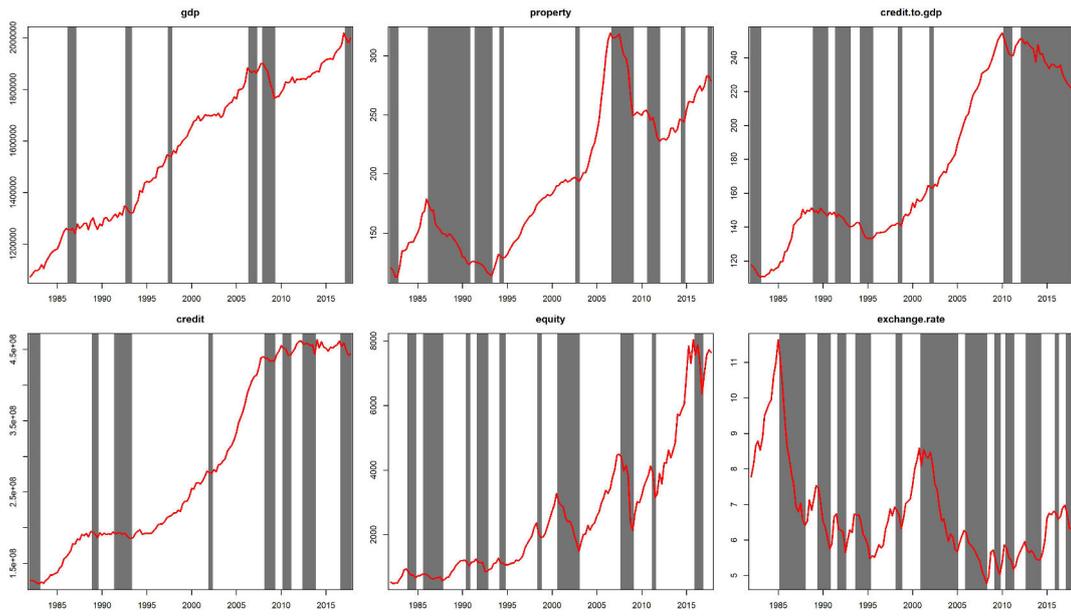


Figure A.3: Denmark

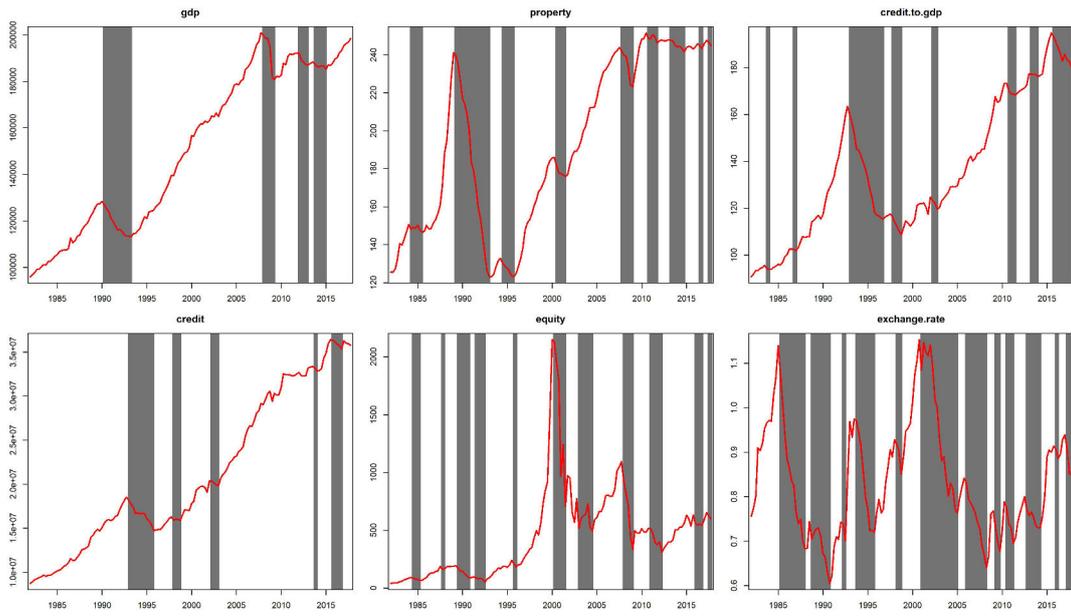


Figure A.4: Finland

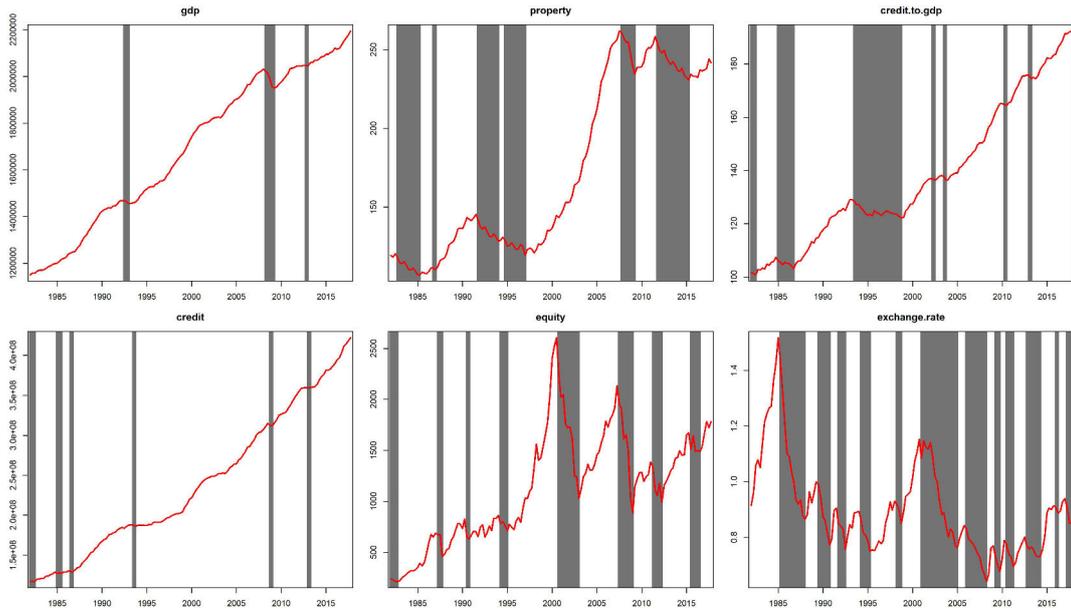


Figure A.5: France

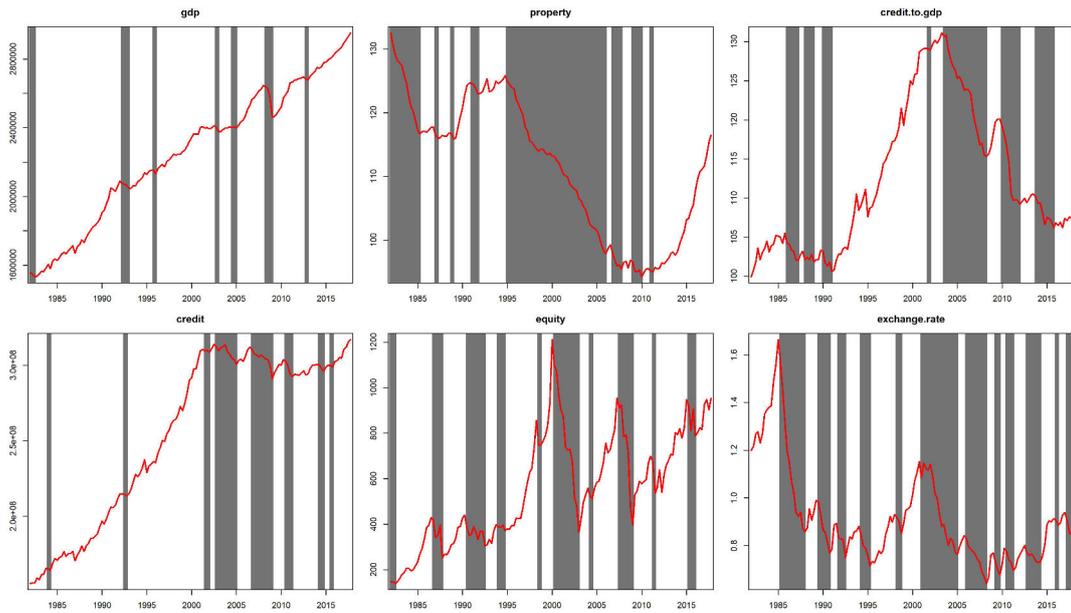


Figure A.6: Germany

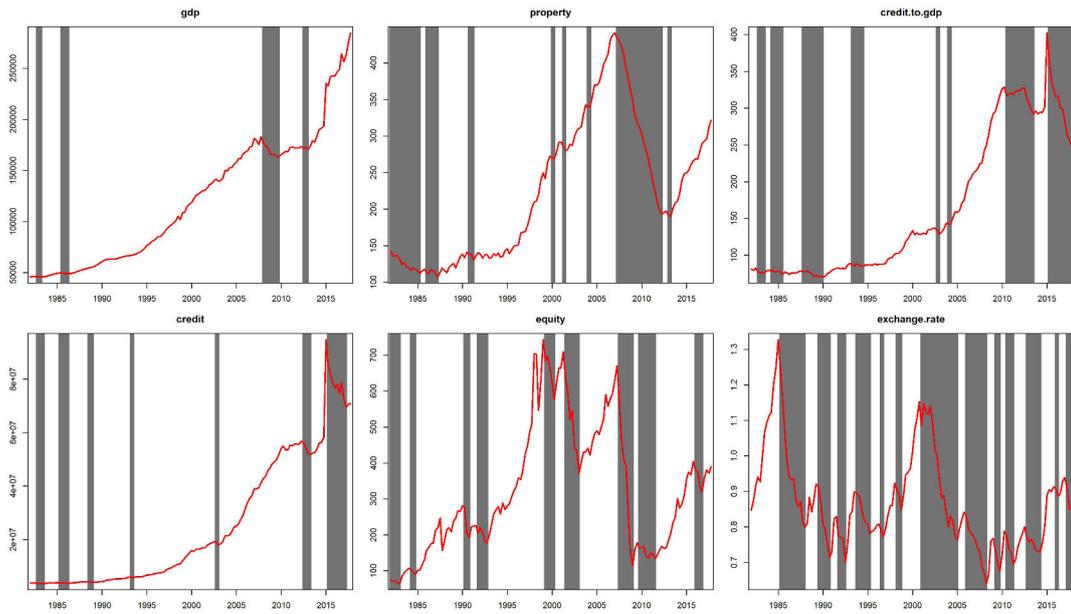


Figure A.7: Ireland

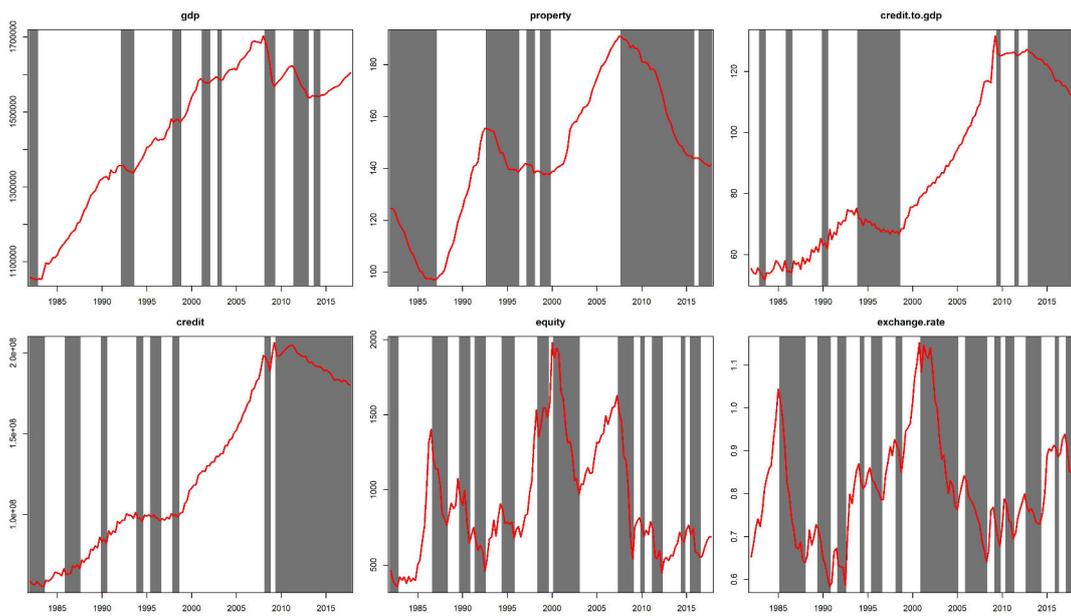


Figure A.8: Japan

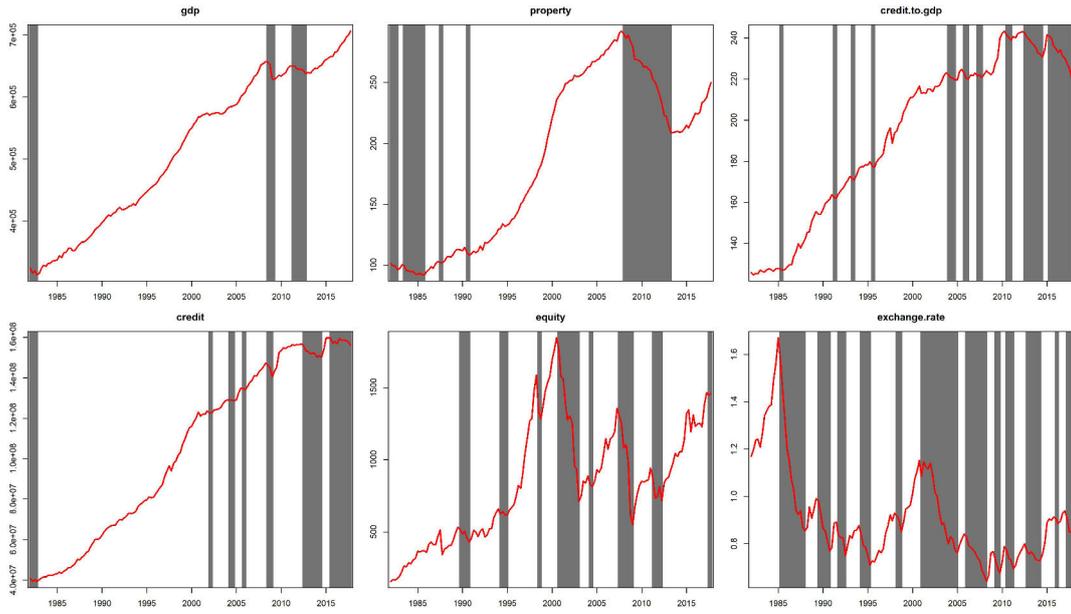


Figure A.9: Netherlands

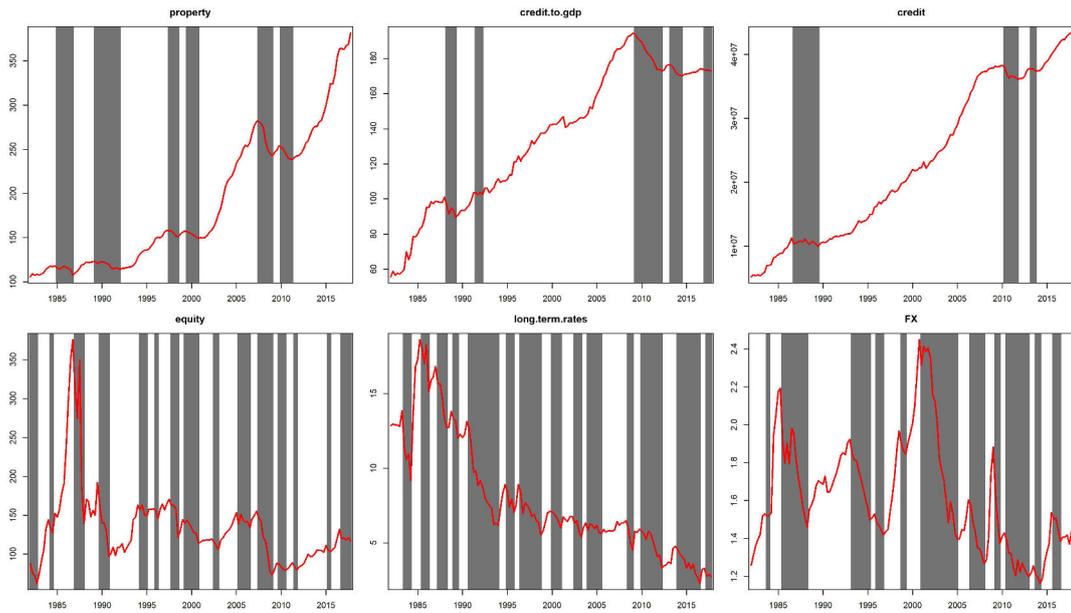


Figure A.10: New-Zealand

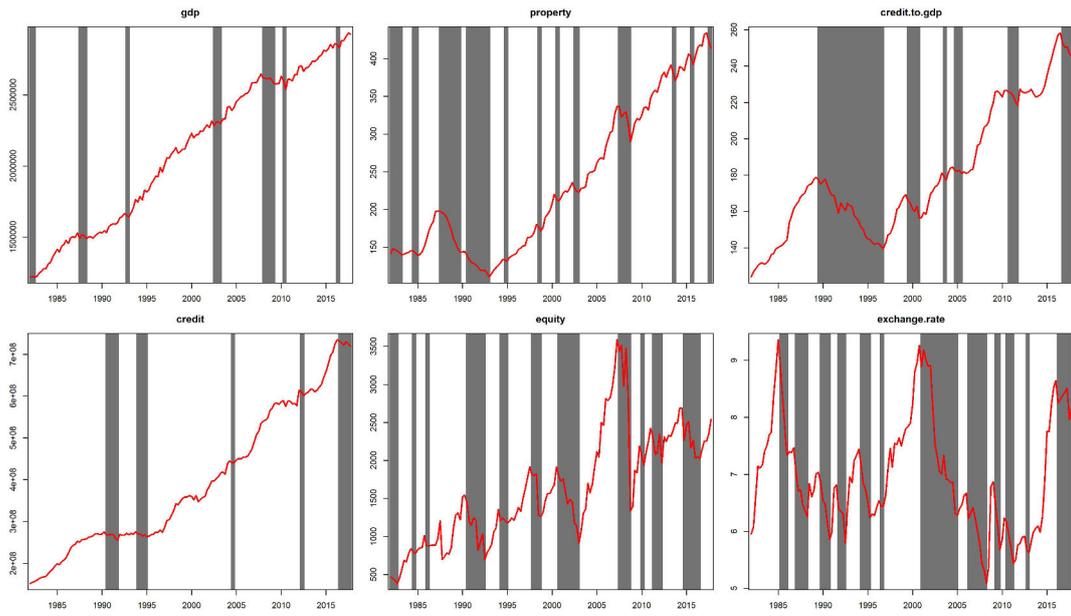


Figure A.11: Norway

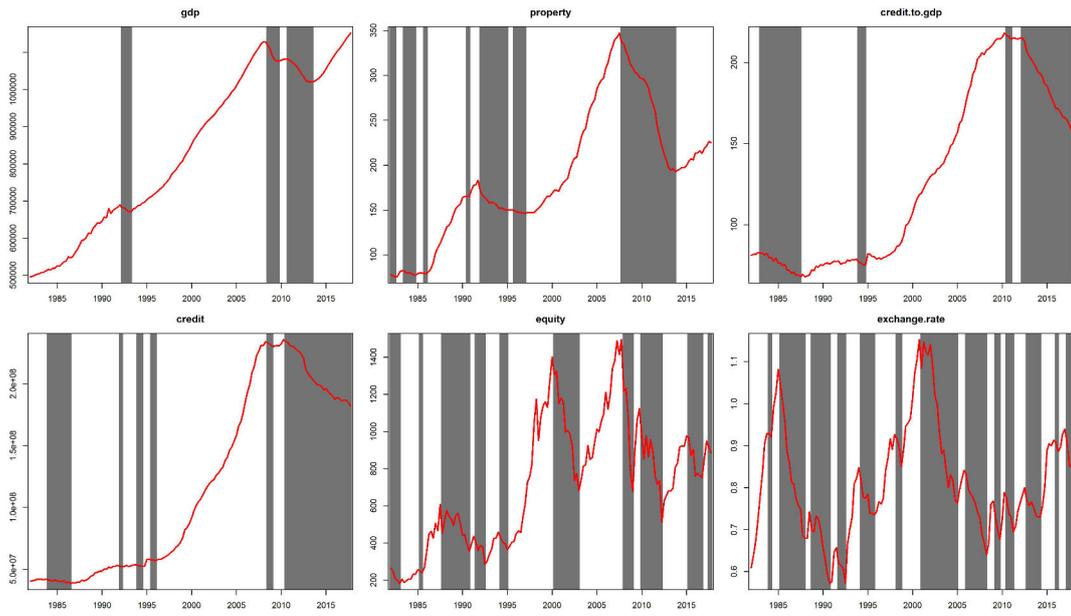


Figure A.12: Spain

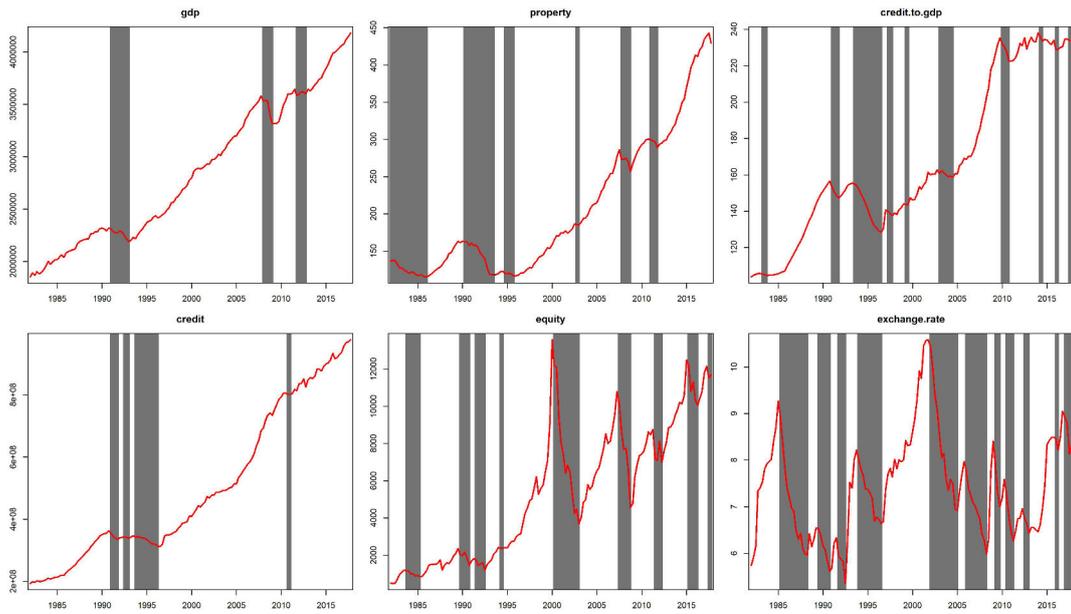


Figure A.13: Sweden

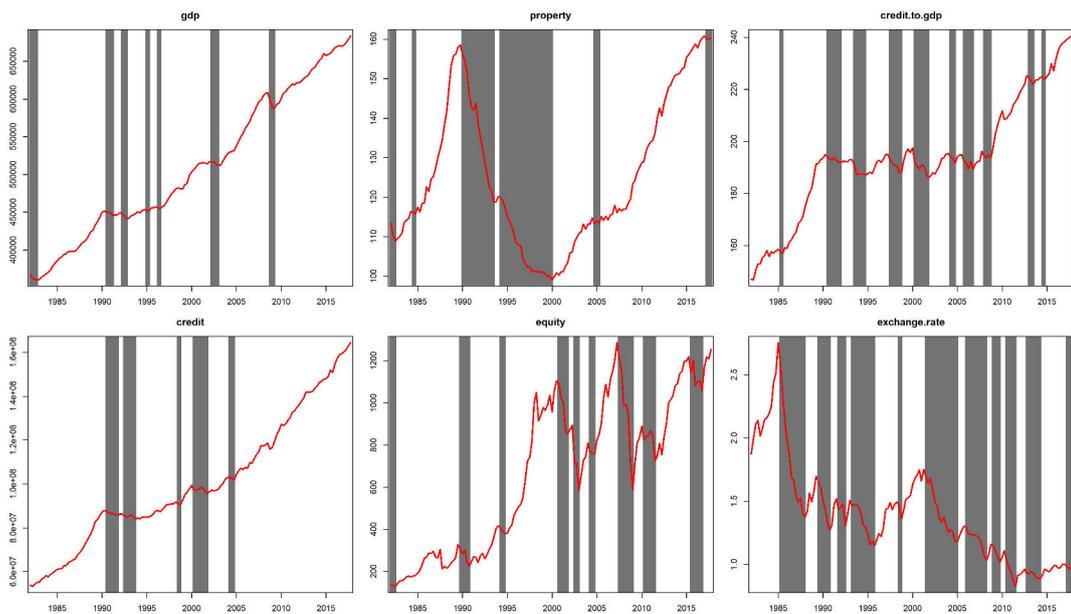


Figure A.14: Switzerland

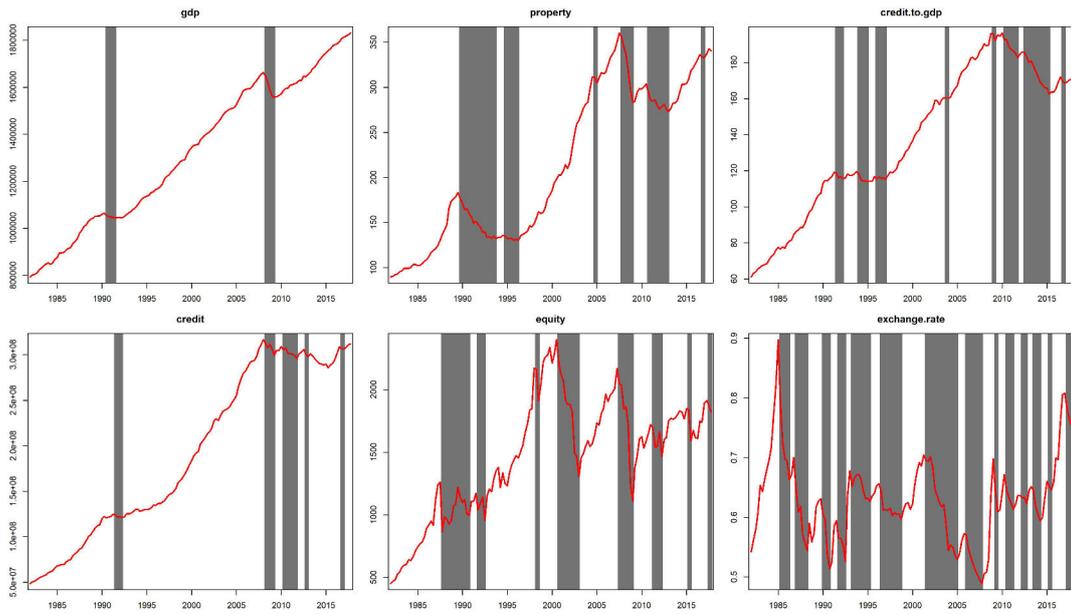


Figure A.15: United Kingdom

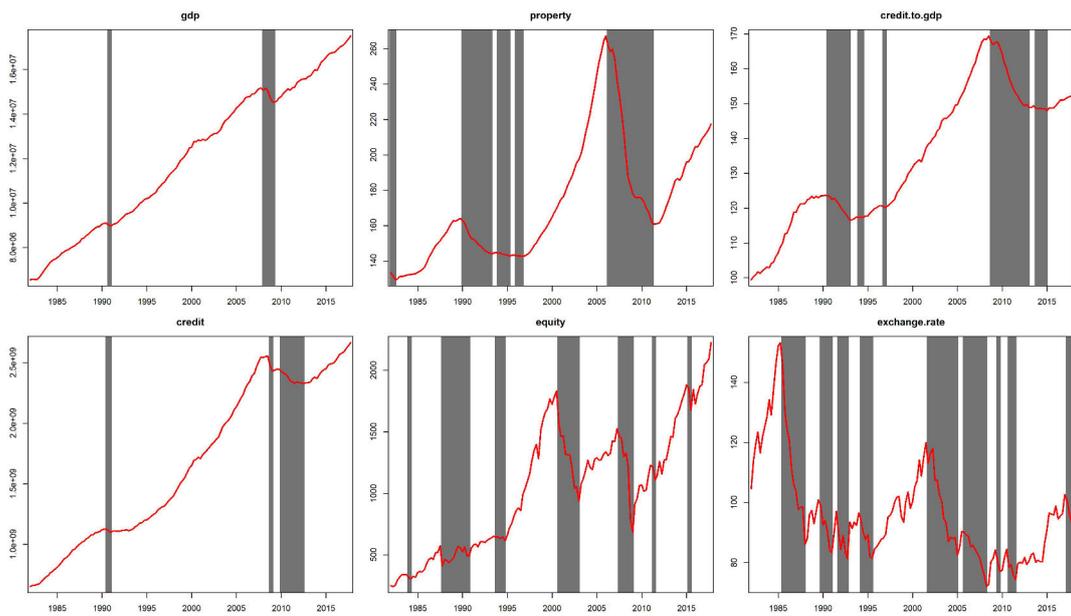


Figure A.16: United States

A.5 The Markov-switching model

We present here the smoothed probabilities (in blue) for each model along with the NBER recessions (in red), as well as residual normality tests for the models including the two selected factors.

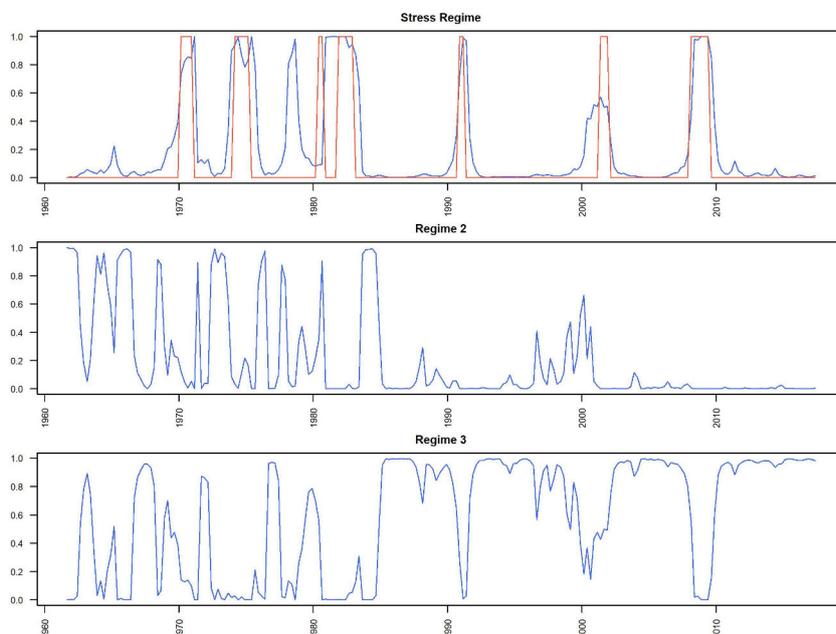


Figure A.17: Smoothed probabilities Factor 1

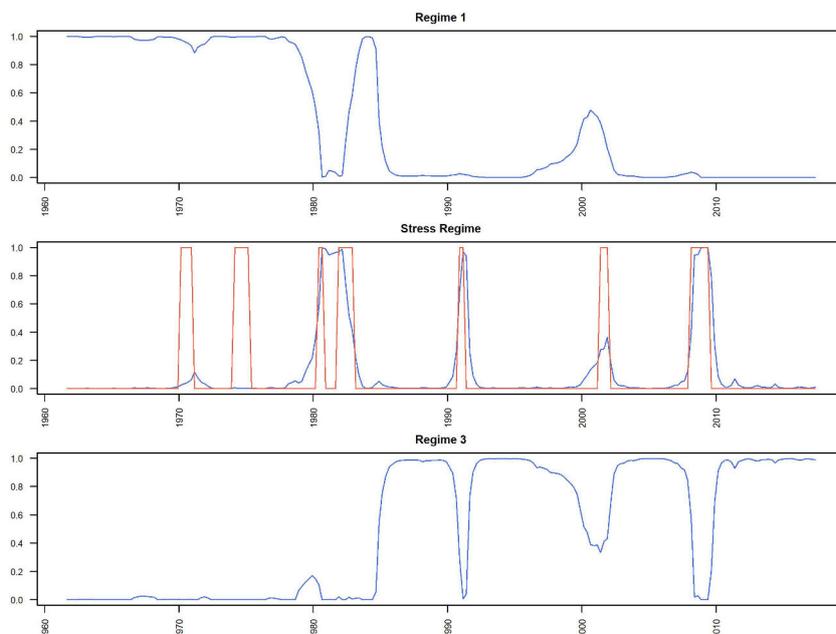


Figure A.18: Smoothed probabilities Factor 2

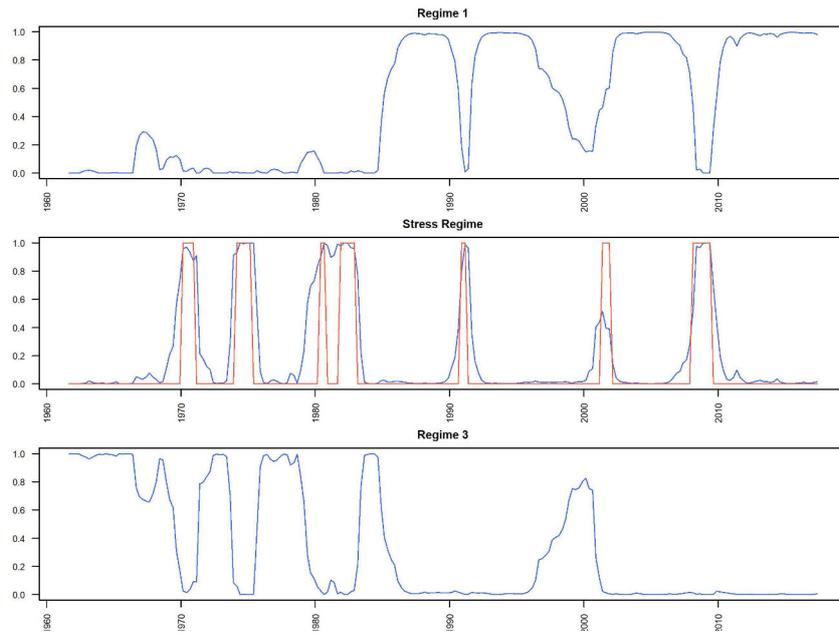


Figure A.19: Smoothed probabilities Factor 3

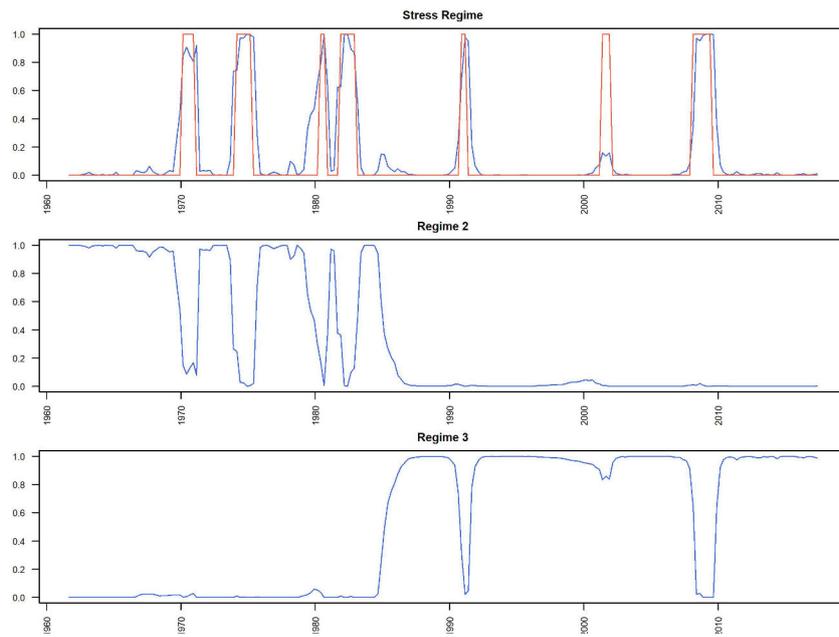


Figure A.20: Smoothed probabilities Factor 4

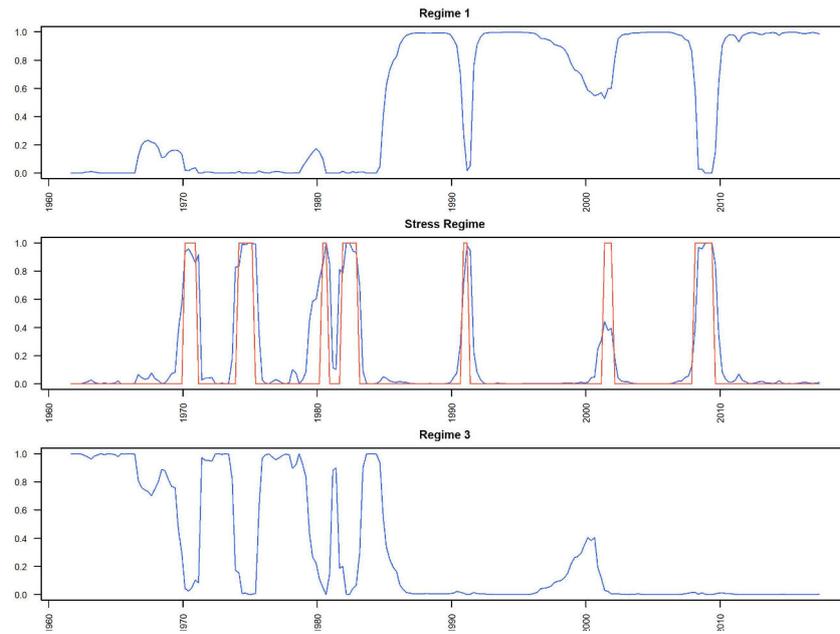


Figure A.21: Smoothed probabilities Factor 5

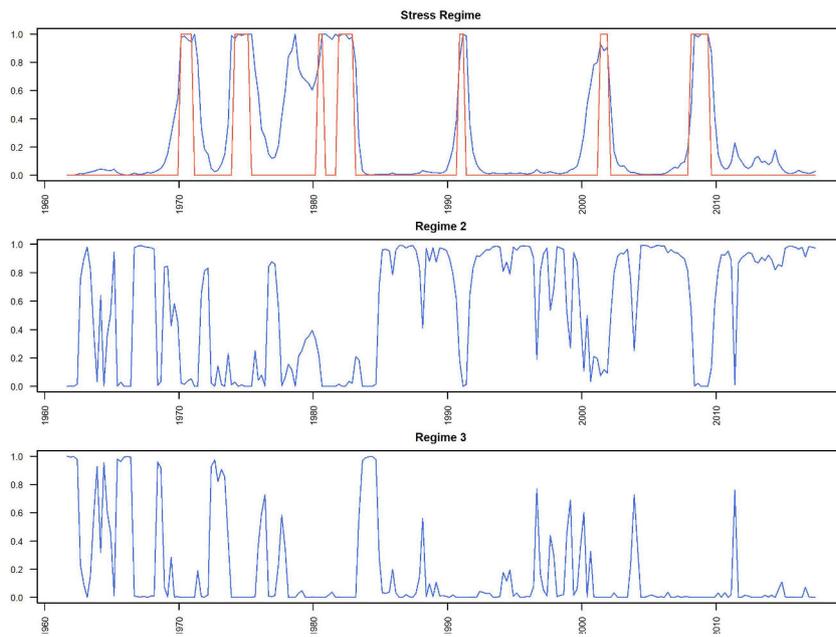


Figure A.22: Smoothed probabilities Factor 6

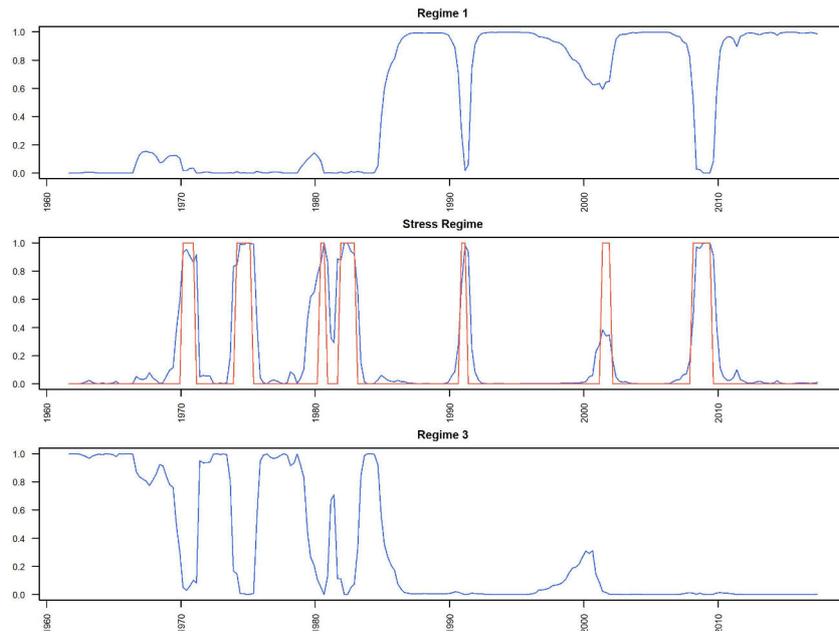


Figure A.23: Smoothed probabilities Factor 7

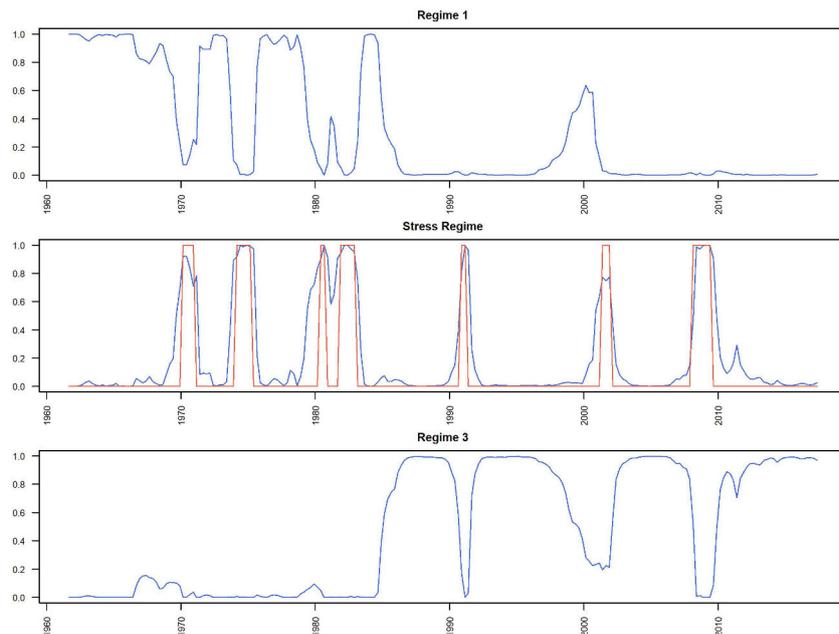


Figure A.24: Smoothed probabilities Factor 8

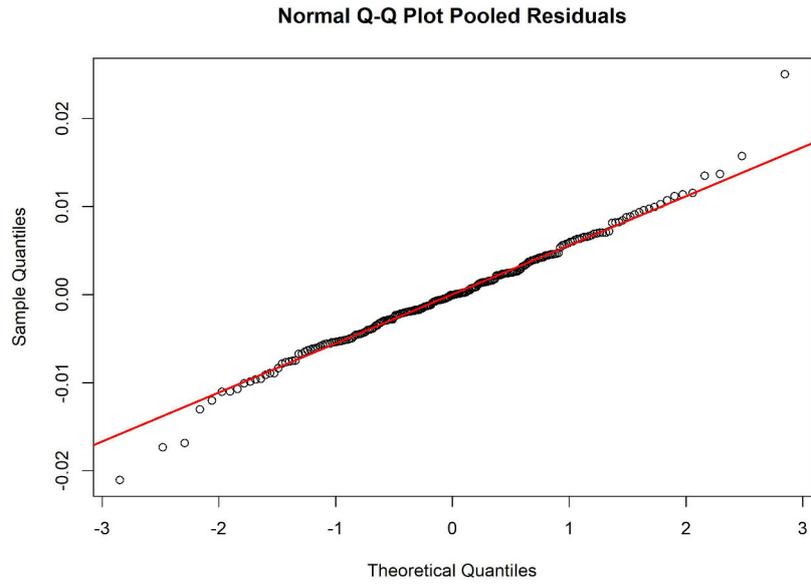


Figure A.25: Residual normality test for Factor 3

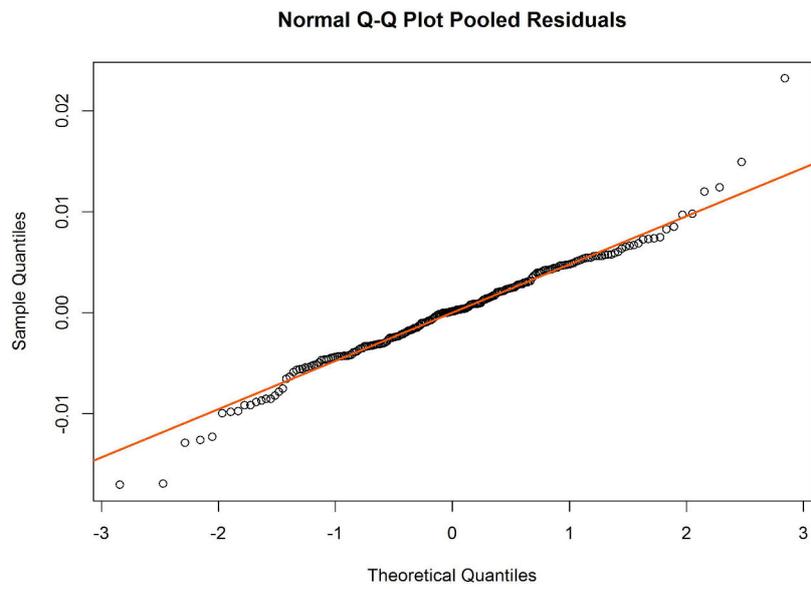
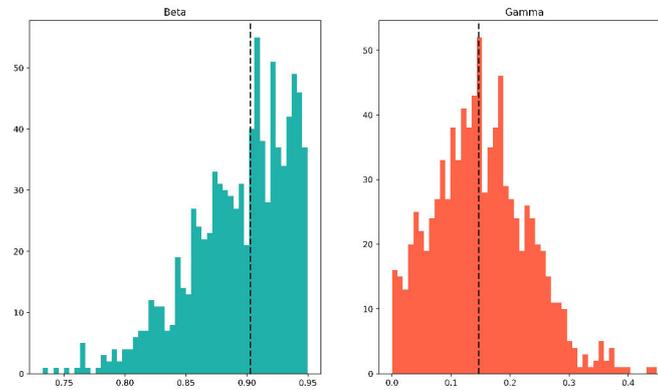


Figure A.26: Residual normality test for factor 8

A.6 Estimation of the output gap with individual variables

Figure A.27: Results with credit-to-GDP only

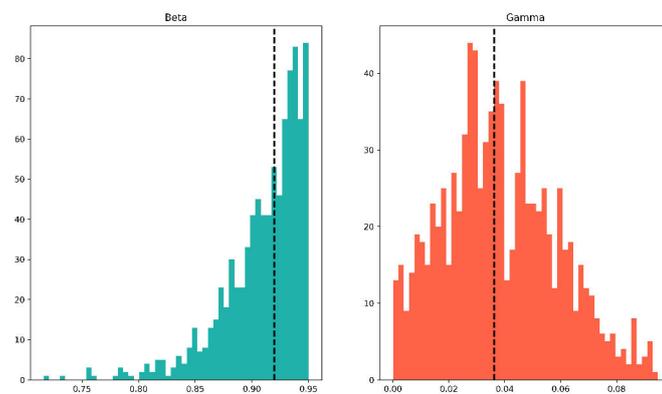


(a) Posterior draws (post burn-in)



(b) Output gap

Figure A.28: Results with property prices only



(a) Posterior draws (post burn-in)



(b) Output gap

Chapter 3

What Does a Financial Shock Do? Let the Data Speak for Themselves

3.1 Introduction

The exercise of disentangling the sources of Business Cycle fluctuations occupies a prominent place in macroeconomic research. The Keynesian theory of the Business Cycle focuses on volatile expectations about future sales and profits, that are inherently impossible to anticipate, as the main source of investment and Business Cycles fluctuations. The Classical view instead argues that output cannot deviate persistently from potential because prices adjust to changes in aggregate demand. Neoclassical economists such as [Kydland and Prescott \[1982\]](#) claim that productivity shocks account for the lion's share of economic fluctuations. None of these approaches to Business Cycle fluctuations assign a prominent role to money and credit, aside from the impact of interest rates on spending. As recalled by [Eckstein and Sinai \[1986\]](#), however, virtually every major recession in the post-WWII period has contained financial ingredients. In the U.S., for instance, credit crunches are crucial factors of the 1966, 1970, 1974, 1980 and 1982 recessions. By the same token, as shown by [Reinhart and Rogoff \[2009b\]](#), the “Big Five” crashes of the 20th century in developed economies¹ were first and foremost financial crises. More recently, the GFC has made it plain that the financial sector could not only amplify shocks arising in the real sector, but also be a source of shocks. The importance of financial factors should however not be confined to recessionary events. As emphasized by [Eckstein and Sinai \[1986\]](#), a large proportion of the Business Cycle's mechanisms are essentially financial. The recognition that financial factors are a key driver of the Business Cycle may also further hone our understanding of standard macroeconomic mechanisms. [Christiano et al. \[2014\]](#) for instance show that the inclusion of financial frictions in New Keynesian models helps to identify shocks hitherto considered as investment shocks as financial shocks.

Notwithstanding the fact that the prominence of financial factors can no longer be disputed, the jury is still out on what exactly is a financial shock. It is unclear for example if a financial shock is akin to an aggregate supply shock, like a productivity or a labor supply shock, or to an aggregate demand shock, like a preference shock or a fiscal shock. In state-

¹Spain 1977, Norway 1987, Finland and Sweden 1991, Japan 1992.

of-the-art Dynamic Stochastic General Equilibrium (DSGE) models, financial shocks can be a supply shock (Meh and Moran [2010]) or a demand shock (Curdia and Woodford [2010]). The theoretical literature considers a large variety of shocks that corresponds to financial shocks. Financial shocks have been defined, *inter alia*, as a shock to the borrowing capacity via a collateral constraint (Iacoviello [2005]) or the external finance premium (Gilchrist et al. [2009b]), a wealth distribution shock (Iacoviello [2015]; Hidakata et al. [2009]), a shock to risk-aversion in the financial sector (Adrian and Shin [2006]), a shock to investor sentiment (Martin and Ventura [2012]), a liquidity shock (Del Negro et al. [2011]), a net worth shock that affect bank's demand for reserves against deposits (Christiano et al. [2014]), a shock to banks capital (Gerali et al. [2010]; Meh and Moran [2010]), a risk shock that affect bank funding technology shock (Christiano et al. [2014]), a shock to bank monitoring productivity (Goodfriend and McCallum [2007]), or a shock to the efficiency of contractual relationships between borrowers and lenders (Nolan and Thoenissen [2009]).

The empirical literature also contributes to the identification of several types of financial shocks. Gambetti and Musso [2017] for instance impose that a credit supply shock affects positively output and credit quantities and negatively lending rates. On the contrary, Fornari and Stracca [2013] are agnostic about whether a financial shock is a demand or a supply shock. The answer depends on the relative reaction of inflation and output, which are left unrestricted. While the two should move in opposite directions after an aggregate supply shock, they should move in unison after an aggregate demand shock. Additionally, Fornari and Stracca [2013] are able to disentangle financial shocks from monetary shocks by restricting the response of the share price of financial firms relative to that of the aggregate stock market index. Another longstanding challenge of this literature is the distinction between financial and uncertainty shocks², which tend to have similar consequences on investment and consumption. After showing that housing shocks have a bigger impact than credit shocks, Furlanetto et al. [2014] demonstrate that financial shocks have larger effects than uncertainty shocks, which are typically modest and short-lived, according to the seminal work of Bloom [2009]. A recent literature also explores the impact of risk shocks, i.e. shocks on future uncertainty and finds them to have substantially larger economic effects than regular, unanticipated risk shocks (Pinter et al. [2013]).

Because it is not clear whether the financial cycle leads (Borio [2014]) or lags (Rünstler and Vlekke [2018]) the Business Cycle, studying the joint dynamics of real and financial factors should allow for a two-way interaction. Vector Autoregressive (VAR) models have been used extensively to set forth macro-financial linkages (Iacoviello [2002]; Neri et al. [2004]; Goodhart and Hofmann [2008]; Chirinko et al. [2008]; Assenmacher-Wesche and Gerlach [2010]; Fornari and Stracca [2013]; Gilchrist and Zakrajsek [2012]). VAR models offer a convenient framework to disentangle impulse and propagating mechanisms. Moreover, under the assumptions of invertibility and covariance stationarity, the Wold representation provides the best linear approximation of the data. Structural Vector Autoregressive (SVAR) models

²Uncertainty may affect investment and consumption if firms face adjustment costs in capital and labor, if agents are risk averse and increase precautionary savings, or if financial constraints tighten in response to higher uncertainty.

additionally offer the benefit, at least theoretically, of being immune to the Lucas critique, in the sense that they make it possible to study shocks that are known by agents ahead of time. In a SVAR model, a financial shock is defined as a movement in a financial variable that cannot be predicted from previous information (an innovation) and that is uncorrelated with contemporary movements of other variables. The underlying assumption is that financial factors have an exogenous component, above and beyond the endogenous reflection of past and current economic activity on financial variables³.

Unlike basic VAR models which are purely statistical tools, the identification of SVAR models however requires additional identification assumptions. A common solution is to restrict the contemporaneous relationship between the variables by assuming that they follow a recursive ordering. Albeit unequivocal in the case of small-scale VARs featuring output, inflation and the policy rate, the distinction between “slow-moving” and “fast-moving” variables is not always clear-cut as far as financial variables are concerned. In this chapter, we use a data-driven approach, called Independent Component Analysis, to uncover the dynamic lead-lag relationships between economic variables and financial variables. We identify a standard SVAR augmented with financial variables for 18 developed countries. We first estimate the recursive ordering suggested by the data individually for each country. The ordering is found to be relatively stable across country, which makes it possible to estimate a panel-SVAR in order to investigate the importance of financial shocks for economic fluctuations.

3.2 The data

Our dataset consists of panel data for 18 OECD countries⁴ from 1982-Q1 to 2017-Q4. The economic side of the VAR is quite standard and is made of output, inflation and the policy rate. This set of variables has been used extensively in small-scale VAR. Since we are dealing with open economies, we also include two exogenous variables that capture global trade and the commodity cycle. For global trade, we use the volume of goods and services exports in dollar. The commodity cycle is proxied by crude oil spot prices converted in local currency for each country. All the data comes from the OECD Main Indicators Database.

As far as financial variables are concerned, the universe of financial shocks that may contribute to the Business Cycle is vast. However, it is well-known that the number of estimated VAR parameters increases geometrically with the number of variables. For the sake of parsimony, we settle for three financial variables that we believe capture distinct but complementary forces. We first include stock prices, which may drive the spending decisions of firms and investors. We also include property prices, which may capture both wealth effects and collateral-based financial accelerator mechanism. Stock prices and property prices

³As recalled by [Bernanke and Mihov \[1998\]](#), “*The emphasis of the VAR-based approach on policy innovations arises not because shocks to policy are intrinsically important, but because tracing the dynamic response of the economy to an [...] innovation provides a mean of observing the effects [...] under minimal identifying assumptions*”.

⁴Australia, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, the U.K. and the U.S.

are complementary as the propensity to consume out of changes in these variables may be different. This can be the case, for instance, if changes in property prices are considered more permanent than changes in stock prices. Finally, the inclusion of credit quantities is self-explanatory given its prominent role in Business Cycle fluctuations. As shown by [Goodhart and Hofmann \[2008\]](#), the deregulation of financial systems in developed countries has reinforced the link between property prices and credit. The joint inclusion of property prices and credit may therefore help to pin down financial accelerator mechanisms.

For credit quantities, we use the credit from all sectors to the private non-financial sector provided by the BIS. Property prices are proxied by nominal residential property prices, also from the BIS. For stock prices we use the MSCI national indexes for each country. The three variables are deflated by the Consumer Price Index. Unit root tests suggest that the variables are nonstationary in levels. We transform the series to achieve stationarity. We take the HP-filtered series of the log of real GDP, the year-on-year growth rate of the CPI and the first-difference of the nominal short-term interest rate. Stock prices and credit quantities are transformed by taking the year-over-year log-difference. For most countries, property prices are integrated of order 2. To ensure consistency across country, we apply the same transformation for all countries and take the first-difference of the year-over-year log-difference. Oil prices and the trade index are included in year-over-year log-difference. A caveat of differencing the data is that it prohibits low frequency variations and focuses on higher frequency correlation. An advantage of doing so, however, is that even if shocks are constrained to have a transitory effects on the differenced variables, that does not discard the possibility that they have a permanent effect on the level of these variables. After the transformations, credit and inflation are still non-stationary for some countries, owing to significant changes in their local means. Therefore, for these two variables, we eliminate very low frequency variations by subtracting the local mean of the transformed variables, estimated with an Unobserved Component Local Level model. The transformed series are plotted in the [Appendix. Table 3.1](#) displays the p-values for the augmented Dickey-Fuller test, where the null hypothesis is the presence of unit root. We finally test for cointegration relationships between the variables in level that would suggest long-run relationship that should be taken into account in the estimation. To this end, we estimate the VAR in levels and apply the test of [Johansen \[1992\]](#). The existence of at least one cointegrating vector can be rejected for all countries.

A natural question when estimating a model on the most recent period is whether to allow for non-linear dynamics around the Great Recession. Based on the contention of [Stock and Watson \[2012\]](#) that the Global Financial Crisis is related to a sequence of unusually large shocks rather than changes in the stochastic macro process, we do not include a dummy variable for the crisis. Ideally, we should allow for stochastic volatility as volatility clustering is no longer a feature that macroeconomists can ignore. However, an efficient estimation of volatility model typically requires a larger number of observations than are available here.

A question of paramount importance when studying VAR is the issue of fundamentalness, or equivalently information sufficiency. A key assumption of SVAR is that the model is large

Table 3.1: P-values for ADF test (H_0 : presence of unit root)

	gdp	cpi	ST.rate	equity	credit	property
US	0.01 **	0.01 **	0.01 **	0.0203 *	0.1863	0.01 **
UK	0.019 *	0.0194 *	0.01 **	0.0169 *	0.0416 *	0.01 **
Japan	0.01 **	0.0147 *	0.01 **	0.0991	0.0796	0.01 **
Germany	0.01 **	0.01 **	0.01 **	0.01 **	0.0193 *	0.01 **
Belgium	0.01 **	0.01 **	0.01 **	0.0156 *	0.0128 *	0.01 **
Canada	0.01 **	0.01 **	0.01 **	0.01 **	0.0121 *	0.01 **
Netherlands	0.01 **	0.01 **	0.01 **	0.0259 *	0.0301 *	0.01 **
France	0.01 **	0.0228 *	0.01 **	0.0146 *	0.01 **	0.01 **
Italy	0.01 **	0.01 **	0.01 **	0.01 **	0.025 *	0.0109 *
Denmark	0.019 *	0.0105 *	0.01 **	0.01 **	0.0804	0.01 **
Sweden	0.01 **	0.0129 *	0.01 **	0.01 **	0.0631	0.01 **
Spain	0.0239 *	0.01 **	0.01 **	0.032 *	0.029 *	0.01 **
Australia	0.01 **	0.01 **	0.01 **	0.01 **	0.0623	0.01 **
Norway	0.0198 *	0.0423 *	0.01 **	0.01 **	0.0109 *	0.01 **
Switzerland	0.01 **	0.0929	0.0183 *	0.01 **	0.0268 *	0.01 **
New.Zealand	0.01 **	0.01 **	0.01 **	0.0574	0.0484 *	0.01 **
Ireland	0.01 **	0.01 **	0.01 **	0.0478 *	0.01 **	0.0135 *

*p<0.05; **p<0.01; ***p<0.001

enough for the one-step ahead forecast errors to contain sufficient information about the structural shocks. In our case, the residuals of the reduced-form VAR are for instance assumed to be a linear combination of structural shocks with economic interpretation. In order to be valid, forecast errors should be as good as those of an individual, a firm, or a policy-maker observing the shocks in real time. Otherwise, the VAR innovations will not span the space of structural shocks, which can therefore no longer be recovered from the reduced-form VAR innovations. An obvious requirement for the analysis to be meaningful is therefore that the variables used in the VAR convey all the relevant information. Such informational sufficiency is implicitly assumed in any SVAR application. [Forni and Gambetti \[2014\]](#) propose a procedure to check whether a specific VAR suffers from this informational problem. The procedure consists in testing if state variables aggregating all relevant economic information Granger cause the variables included in the VAR. If so, the VAR suffers for information insufficiency. This being beyond the scope of this chapter, informational sufficiency is taken for granted here.

3.3 The model

VAR models allow to decompose changes in the model variables between a systematic component, based on past movements of itself and other variables and an innovation component, i.e. one-step ahead forecast error, that are unpredictable from past information. Consider the following N -variables reduced-form model:

$$Y_t = A_1 y_{t-1} + \dots + A_p Y_{t-p} + u_t \Leftrightarrow A(L)Y_t = u_t \quad \text{with } A(L) = I_K - A_1 L - A_2 L^2 - \dots - A_p L^p$$

where $u_t = Y_t - E_{t-1}[Y_t|Y_1, \dots, Y_{t-1}] \sim (0, \Sigma_u)$ is a $N \times 1$ vector of homoskedastic white noise errors, i.e. one-step ahead prediction error based on information $\{Y_1, \dots, Y_{t-1}\}$.

We assume that condition of stability holds, that is:

$$\det(I_K - A_1z - \dots - A_pz^p) \neq 0 \quad \text{for all } z \in \mathbb{R} \quad \text{such that } |z| \leq 1$$

The existence of a reduced-form representation of the VAR with finite order and fixed coefficients can be derived from the Wold representation theorem assuming linearity, stationarity and invertibility of the resulting moving average representation. The Wold representation, which is the best linear approximation of the data, yields:

$$Y_t = A(L)^{-1}u_t \Leftrightarrow Y_t = \sum_{j=0}^{\infty} \Psi_j u_{t-j}$$

where

$$\Psi_0 = I_K \quad \Psi_s = \sum_{j=1}^s \Psi_{s-j} A_j \quad \text{for } s = 1, 2, \dots \quad \text{and } A_j = 0 \quad \text{for } j > p$$

In general, the reduced-form residual covariance matrix Σ_u will be non-diagonal. In that case, reduced-form innovations will not be structural, in the sense that it is not possible to study the impact of an impulse on one of the variables, keeping all other shocks constant. We therefore consider a second model to describe the Data Generating Process (DGP), the structural model, whereby shocks can be deemed structural and can be interpreted economically:

$$B_0 Y_t = B_1 Y_{t-1} + \dots + B_p Y_{t-p} + \varepsilon_t \quad \text{with } \varepsilon_t \sim (0, \Sigma_\varepsilon); \quad A_i = B_0^{-1} B_i \quad \text{and } u_t = B_0^{-1} \varepsilon_t$$

Structural shocks ε_t are unpredictable from past information and mutually orthogonal⁵. As a result, in that framework, a financial shock will be defined as an unexpected shock to housing prices, stock prices or credit quantities, that cannot be explained by past economic conditions and which is uncorrelated with other shocks. However, the structural model cannot be estimated equation by equation owing to simultaneity. The identification problem consists in finding a mapping between the reduced-form VAR that can be estimated but not be used for policy analysis and the Structural VAR that cannot be estimated but can be used for policy analysis. The knowledge of B_0 is sufficient to compute the B_i 's and allows for a direct mapping between the structural and the reduced-form model. The identification of B_0^{-1} can be done through the estimated reduced-form residual covariance matrix $\hat{\Sigma}_u$. One way to identify B_0^{-1} is to use the estimated covariance matrix of the reduced-form residuals.

$$\begin{aligned} \hat{\Sigma}_u &= E(\hat{u}_t \hat{u}_t') = B_0^{-1} E(\varepsilon_t \varepsilon_t') (B_0^{-1})' \\ &= B_0^{-1} \Sigma_\varepsilon (B_0^{-1})' \\ &= B_0^{-1} (B_0^{-1})' \end{aligned}$$

⁵An important assumption of this type of SVAR model is that there are as many structural shocks as variables.

where we have assumed without loss of generality that Σ_ε is the identity matrix I_N . Unfortunately, $\hat{\Sigma}_u$ alone is not sufficient to uniquely characterize the model parameters. The estimation of $\hat{\Sigma}_u$ yields $N(N + 1)/2$ free parameters while we would like to estimate the N^2 parameters in B_0^{-1} . The system is therefore under-identified and cannot be solved by a pure statistical tool without additional economic assumptions.

A common approach for the identification problem is to assume contemporaneous acyclicity, meaning that all the variables can be ordered from the more “slow-moving”, or more exogenous, to the more “fast-moving”, or more endogenous. A variable is said to be more exogenous than another variable when the former is not allowed to react contemporaneously to the latter. This means that we impose a particular causal chain rather than learning about causal relationships from the data. Of course, if the underlying DGP does not follow a recursive ordering in the first place, the model will be flawed regardless of the selected ordering. Additionally, the ordering does not make economic sense without a plausible economic interpretation. However, albeit relatively undisputed in small-scale VARs featuring output, inflation and the policy rate, economic theory is of little help regarding the ordering of financial variables. New-Keynesian models usually provide theoretical underpinnings for the identification restrictions in Structural VAR models. However, due to design limitations in terms of complexity, these models are relatively silent when several financial variables are included. As a result, the VAR literature that identifies financial shocks recursively usually resorts to restrictions based on intuition. The financial variable is typically ordered below macroeconomic variables on the premise that financial markets react instantaneously to new information (see [Bagliano and Morana \[2012\]](#); [Hubrich and Tetlow \[2015\]](#), to cite but a few). However, this is of little guidance when it comes to housing prices, which are inherently stickier than other asset prices and credit quantities. [Goodhart and Hofmann \[2008\]](#) for instance order property prices after output, inflation and the policy rate, but before money and credit, which are assumed to be less sticky. To motivate the relative ordering between property prices and interest rates, [Musso et al. \[2011\]](#) claim that mortgage interest rates are a lagged function of the policy rate and that property prices respond with a lag to changes in interest rates. In [Gilchrist and Zakrajsek \[2012\]](#), the excess bond premium, is ordered after output and inflation and before risk-free interest rates, while stock prices are ordered last. These well-founded motivations notwithstanding, imposing a recursive ordering is problematic as the economic interpretation of such VAR typically hinges crucially on the selected order.

Instead of choosing a specific ordering, we prefer to let the data speak and use a recent method that bears upon the non-Gaussian structure of the data ([Shimizu et al. \[2006\]](#); [Hyvärinen et al. \[2010\]](#)) to overcome the identifiability problem. This method, called Independent Component Analysis (ICA), comes from the signal processing literature and has been recently used for the identification of SVAR ([Moneta et al. \[2013\]](#); [Guerini et al. \[2017\]](#); [Gouriéroux et al. \[2017\]](#)). Unlike Principal Component Analysis, which transforms the original space into linearly uncorrelated latent components, ICA minimizes all statistical dependencies between

the estimated components⁶. Restating the problem in SVAR terms, the approach assumes that reduced-form residuals have been combined by a mixing matrix B_0 to yield a linear combination of the structural shocks, such that $u_t = B_0^{-1}\varepsilon_t$, whereby the ε_t 's are mutually statistically independent. The assumption of statistical independence of ε_t 's, which cannot be tested statistically, can be theoretically justified by the fact that they represent distinct economic shocks. Statistical independence cannot be tested empirically as this would require infinite data. Non-gaussianity serves as a proxy for statistical independence. As shown by Comon [1994], if there exists a representation with non-Gaussian⁷ statistically independent components, then the representation is unique up to permutation, sign and scaling. Financial variables are likely to exhibit non-gaussianity, owing for instance to heteroskedasticity (Campbell et al. [1997]). Under the assumptions of statistical independence and non-gaussianity, the estimation of the independent components can be done by maximizing the non-Gaussianity of the estimated components, or equivalently minimizing the mutual information among them. The algorithm FastICA of Hyvärinen [1999], Hyvärinen and Oja [2000] offers a computationally efficient way to maximize non-Gaussianity of the rotated components. The algorithm searches among all the possible linear combinations of reduced-form residuals the one that minimizes mutual information⁸. However, the Independent Component Analysis only identifies the components up to permutation, sign and scaling because the connection between the variables and the structural shock is lost in the estimation. The assumption of contemporaneous acyclicity allows to address this indeterminacy and to map the ε_t 's and the u_t 's with a one-to-one relationship. For that purpose, we use the VAR-LiNGAM algorithms, which adapts the LiNGAM (linear non-Gaussian, acyclic model) algorithm of Shimizu et al. [2006] to a SVAR context.

Once B_0 is identified, impulse responses functions can be estimated. We first compute the Structural Moving Average (SMA) representation of Y_t by substituting $u_t = B_0^{-1}\varepsilon_t$ into the Wold representation of the reduced-form model:

$$y_t = \mu + \Psi(L)B_0^{-1}\varepsilon_t = \mu + \Theta(L)\varepsilon_t \quad \text{with } \mu = (I_K - A_1)^{-1}A_0$$

and

$$\Theta(L) = \sum_{k=0}^{\infty} \Theta_k L^k = \Psi(L)B^{-1} = B^{-1} + \Psi_1 B^{-1}L + \dots$$

$$\begin{bmatrix} y_{1,t} \\ \vdots \\ y_{K,t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \vdots \\ \mu_K \end{bmatrix} + \begin{bmatrix} \theta_{1,1}(0) & \dots & \theta_{1,K}(0) \\ \vdots & \ddots & \vdots \\ \theta_{K,1}(0) & \dots & \theta_{K,K}(0) \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t} \\ \vdots \\ \varepsilon_{K,t} \end{bmatrix} + \begin{bmatrix} \theta_{1,1}(1) & \dots & \theta_{1,K}(1) \\ \vdots & \ddots & \vdots \\ \theta_{K,1}(1) & \dots & \theta_{K,K}(1) \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1} \\ \vdots \\ \varepsilon_{K,t-1} \end{bmatrix} + \dots$$

Now we can compute the impulse response functions by considering the SMA representation at time $t + s$:

⁶While uncorrelatedness of the shocks ε_t only requires that the covariance matrix $E(\varepsilon_t \varepsilon_t^T)$ is diagonal, full statistical independence requires that the joint probability density equals the product of its marginal, i.e. $f(\varepsilon_{1t}, \dots, \varepsilon_{Kt}) = f(\varepsilon_{1t}) \times \dots \times f(\varepsilon_{Kt})$.

⁷More precisely, there can be no more than one gaussian element.

⁸Mutual information equals zero if and only if the variables are independent.

$$\begin{bmatrix} y_{1,t+s} \\ \vdots \\ y_{K,t+s} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \vdots \\ \mu_K \end{bmatrix} + \begin{bmatrix} \theta_{1,1}(0) & \dots & \theta_{1,K}(0) \\ \vdots & \ddots & \vdots \\ \theta_{K,1}(0) & \dots & \theta_{K,K}(0) \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t+s} \\ \vdots \\ \varepsilon_{K,t+s} \end{bmatrix} + \dots + \begin{bmatrix} \theta_{1,1}(1) & \theta_{1,K}(1) \\ \vdots & \vdots \\ \theta_{K,1}(1) & \theta_{K,K}(1) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \vdots \\ \varepsilon_{Kt} \end{bmatrix} + \dots$$

The impulse response function for variable i to a structural shock on variable j after s periods corresponds to the response of $y_{i,t+s}$ to a one-time impulse in $y_{j,t}$, with all other variables dated t or earlier held constant:

$$\frac{\partial y_{i,t+s}}{\partial \varepsilon_{j,t}} = \theta_{i,j}(s)$$

A major constraint, when estimating a VAR with macro data at the quarterly frequency is the lack of degrees of freedom. Therefore, estimating country-specific VAR yields very imprecise estimates of impulse responses and does not allow to reject the null hypothesis of financial shocks having no impact on output. Panel VAR models are richer than simple VAR models because they add a cross-sectional dimension which increases the number of degrees of freedom and the efficiency of the estimates so obtained (smaller standard errors). Panel VAR have therefore been used extensively in the literature on macro-financial linkages (see, for instance, [Ciccarelli et al. \[2012\]](#)).

Panel VAR allow to model three types of interdependences across units: dynamic interdependence, whereby unit-specific regressors respond to lags of all endogenous variables of all unit; static interdependence, whereby the residuals of unit specific models are allowed to correlate across units; and cross-sectional heterogeneity, which allows the VAR coefficients and residual variances to be unit-specific. In practice, owing to limited degrees of freedom, some of these properties are relaxed. In the baseline specification we relax all the assumptions outlined herein and use the pooled estimator. On the face of it, the pooled estimation may seem restrictive, chiefly because it assumes a common macro-dynamic patterns and attributes cross-country differences to idiosyncratic one-time shocks. As shown by [Gavin and Theodorou \[2005\]](#), however, the pooled estimation allows to uncover economic relationships that are only weakly present at the country-level. Moreover, they show that out-of-sample forecasts from the common model outperform significantly forecasts from the individual country models, even when the homogeneity assumption is rejected at the country-level. Additionally, by decreasing the number of parameters relative to number of observations, the pooled estimation reduces the sampling error caused by observing a sample instead of the whole population and therefore improves the statistical power of the estimation.

We consider a model with N endogenous variables, K number of units, T observations, m exogenous variables (x_t) and p lags:

$$\begin{pmatrix} Y_{1,t} \\ Y_{2,t} \\ \vdots \\ Y_{N,t} \end{pmatrix} = \begin{pmatrix} A_1 & 0 & \dots & 0 \\ 0 & A_1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \dots & A_1 \end{pmatrix} \begin{pmatrix} Y_{1,t-1} \\ Y_{2,t-1} \\ \vdots \\ Y_{N,t-1} \end{pmatrix} + \dots + \begin{pmatrix} A_p & 0 & \dots & 0 \\ 0 & A_p & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \dots & A_p \end{pmatrix} \begin{pmatrix} Y_{1,t-p} \\ Y_{2,t-p} \\ \vdots \\ Y_{N,t-p} \end{pmatrix} + \begin{pmatrix} C \\ C \\ \vdots \\ C \end{pmatrix} x_t + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \vdots \\ \varepsilon_{N,t} \end{pmatrix}$$

and

$$\Sigma = \begin{pmatrix} \Sigma_c & 0 & \dots & 0 \\ 0 & \Sigma_c & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \dots & \Sigma_c \end{pmatrix}$$

Consider individual unit models:

$$Y_{i,t} = A_1 Y_{i,t-1} + \dots + A_p Y_{i,t-p} + C x_t + \epsilon_{i,t}$$

Stacking the model over the K units:

$$Y_t = X_t B + \mathcal{E}$$

with:

$$Y_t = \begin{pmatrix} Y'_{1,t} \\ Y'_{2,t} \\ \vdots \\ Y'_{N,t} \end{pmatrix} \quad X_t = \begin{pmatrix} Y'_{1,t-1} & \dots & Y'_{1,t-p} & x'_t \\ Y'_{2,t-1} & \dots & Y'_{2,t-p} & x'_t \\ \vdots & \vdots & \vdots & \vdots \\ Y'_{N,t-1} & \dots & Y'_{N,t-p} & x'_t \end{pmatrix} \quad B = \begin{pmatrix} A'_1 \\ \vdots \\ A'_p \\ C' \end{pmatrix} \quad \mathcal{E}_t = \begin{pmatrix} \epsilon'_{1,t} \\ \epsilon'_{2,t} \\ \vdots \\ \epsilon'_{N,t} \end{pmatrix}$$

Stacking over the T time periods:

$$Y = X B + \mathcal{E}$$

with

$$Y = \begin{pmatrix} Y_1 \\ \vdots \\ Y_T \end{pmatrix} \quad X = \begin{pmatrix} X_1 \\ \vdots \\ X_T \end{pmatrix} \quad B = \begin{pmatrix} \mathcal{E}_1 \\ \vdots \\ \mathcal{E}_T \end{pmatrix}$$

Reformulating the model in vectorised form:

$$y = \bar{X} \beta + \varepsilon$$

with

$$y_i = \text{vec}(Y) \quad \bar{X} = (I_N \otimes X) \quad \beta = \text{vec}(B) \quad \varepsilon = \text{vec}(\mathcal{E})$$

and

$$\varepsilon \sim \mathcal{N}(0, \hat{\Sigma}), \quad \text{with } \hat{\Sigma} = \Sigma_c \otimes I_{KT}$$

The pooled estimator can be estimated from a Bayesian perspective. The likelihood of the model is given by:

$$f(y|\beta, \hat{\Sigma}) \propto |\hat{\Sigma}|^{\frac{1}{2}} \exp\left(-\frac{1}{2}(y - \bar{X}\beta)' \hat{\Sigma}^{-1} (y - \bar{X}\beta)\right)$$

The prior for β is assumed to be multivariate normal and the prior for Σ_c is inverse Wishart. Using Bayes' rule, we combine the likelihood function with the prior distributions to obtain the posterior distribution $\pi(\beta, \Sigma_c|y)$. Then marginalising for β and Σ , we obtain the posterior

distribution $\pi(\beta|y)$ and $\pi(\Sigma_c|y)$.

As a robustness check, we also consider the Mean-Group estimator. If the true Data Generating Process exhibits different slope parameters across countries, pooling will introduce aggregation/heterogeneity bias, even in large samples. As shown by [Pesaran and Smith \[1995\]](#), pooled estimators yield inconsistent estimates of the true cross-section mean of the parameters. In particular, the within and between estimators are inconsistent because the regressors are correlated with the error term when dynamic heterogeneity arises. The mean-group estimator, which is the arithmetic average of the country-specific estimates, is inefficient relative to the pooled estimator under dynamic homogeneity, but gives consistent estimates of the average dynamic effect of shocks if dynamic heterogeneity is present. Mean-group estimation allows for cross sectional heterogeneity, i.e. for slope (different response to shocks) and variance (shocks with different magnitude) heterogeneity.

The model has the following form:

$$\begin{pmatrix} Y_{1,t} \\ Y_{2,t} \\ \vdots \\ Y_{N,t} \end{pmatrix} = \begin{pmatrix} A_{1,1} & 0 & \dots & 0 \\ 0 & A_{2,1} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \dots & A_{N,1} \end{pmatrix} \begin{pmatrix} Y_{1,t-1} \\ Y_{2,t-1} \\ \vdots \\ Y_{N,t-1} \end{pmatrix} + \dots + \begin{pmatrix} A_{1,p} & 0 & \dots & 0 \\ 0 & A_{2,p} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \dots & A_{N,p} \end{pmatrix} \begin{pmatrix} Y_{1,t-p} \\ Y_{2,t-p} \\ \vdots \\ Y_{N,t-p} \end{pmatrix} \\ + \begin{pmatrix} C_{1,t} \\ C_{2,t} \\ \vdots \\ C_{N,t} \end{pmatrix} x_t + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \vdots \\ \varepsilon_{N,t} \end{pmatrix}$$

and

$$\Sigma = \begin{pmatrix} \Sigma_1 & 0 & \dots & 0 \\ 0 & \Sigma_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \dots & \Sigma_N \end{pmatrix}$$

Consider individual unit models:

$$Y_{i,t} = A_{i,1}Y_{i,t-1} + \dots + A_{i,p}Y_{i,t-p} + C_i x_t + \varepsilon_{i,t}$$

where $\varepsilon_{i,t} \sim \mathcal{N}(0, \Sigma_i)$.

Stacking the model over the T sample periods:

$$Y_i = X_i B_i + \mathcal{E}_i$$

with:

$$Y_i = \begin{pmatrix} Y'_{i,1} \\ Y'_{i,2} \\ \vdots \\ Y'_{i,T} \end{pmatrix} \quad X_i = \begin{pmatrix} Y'_{i,0} & \cdots & Y'_{i,1-p} & x'_1 \\ Y'_{i,1} & \cdots & Y'_{i,2-p} & x'_2 \\ \vdots & \ddots & \vdots & \vdots \\ Y'_{i,T-1} & \cdots & Y'_{i,T-p} & x'_T \end{pmatrix} \quad B_i = \begin{pmatrix} A'_{i,1} \\ \vdots \\ A'_{i,p} \\ C'_i \end{pmatrix} \quad \mathcal{E}_i = \begin{pmatrix} \varepsilon'_{i,1} \\ \varepsilon'_{i,2} \\ \vdots \\ \varepsilon'_{i,T} \end{pmatrix}$$

Reformulating the model in vectorised form:

$$y_i = \bar{X}_i \beta_i + \varepsilon_i$$

with

$$y_i = \text{vec}(Y_i) \quad \bar{X}_i = (I_N \otimes X_i) \quad \beta_i = \text{vec}(B_i) \quad \varepsilon_i = \text{vec}(\mathcal{E}_i)$$

The mean-group estimator model assumes that for each unit i , β_i can be expressed as:

$$\beta_i = b + b_i$$

with $b_i \sim \mathcal{N}(0, \Sigma_b)$, which means that the coefficients of the VAR in different units differ but are drawn from a distribution with constant mean and variance across units. To estimate b , which is the parameter of interest, [Pesaran and Smith \[1995\]](#) obtain an estimate of β_i for each unit by standard OLS:

$$\hat{\beta}_i = (\bar{X}'_i \bar{X}_i)^{-1} \bar{X}'_i y_i$$

Then the mean-group estimator for b is:

$$\hat{b} = \frac{1}{N} \sum_{i=1}^N \hat{\beta}_i$$

And the standard error for the mean-group estimator is given by:

$$\Sigma_b = \frac{1}{N(N-1)} \sum_{i=1}^N (\hat{\beta}_i - \hat{b})(\hat{\beta}_i - \hat{b})'$$

For each unit, the mean-group estimate of the residual variance-covariance matrix is:

$$\hat{\Sigma}_i = \frac{1}{T - NKp - m - 1} \mathcal{E}'_i \mathcal{E}_i$$

And the mean-group estimator of Σ is given by:

$$\hat{\Sigma} = \frac{1}{N} \sum_{i=1}^N \hat{\Sigma}_i$$

3.4 Results

We first fit country-specific VAR models. For each country, the number of lags is chosen according to the Akaike Information Criterion (AIC). The stability of each model is assessed by checking that its reverse characteristic polynomial has no roots outside the complex circle,

or equivalently that all eigenvalues of the companion coefficient matrix have modulus lower than 1. [Table 3.2](#) shows the highest eigenvalue for each country.

Table 3.2: Highest eigenvalues of the companion matrix

US	0.968
UK	0.962
Japan	0.945
Germany	0.951
Belgium	0.957
Canada	0.906
Netherlands	0.957
France	0.960
Italy	0.936
Denmark	0.969
Sweden	0.934
Spain	0.959
Australia	0.945
Norway	0.966
Switzerland	0.955
New.Zealand	0.961
Ireland	0.938

Before using the Independent Component Analysis algorithm, we assess the degree of non-Gaussianity of the reduced-form VAR residuals with the Shapiro-Wilk test. The tests ([Table 3.3](#)) suggest that except for the forecast errors related to the policy rate we can reject the null hypothesis that reduced-form residuals are normally distributed. There is no threshold for the degree of non-normality that is required to make the ICA reliable and the asymptotic variance of the Independent Component estimates will be a function of the non-Gaussianity of the components. [Table 3.3](#) shows the ordering suggested by the algorithm for each country.

The country-specific orderings reveal a number of interesting facts. First, for most countries, GDP is ordered first, meaning that it does not react contemporaneously to shocks to other variables than itself. The second rank is more disputed, with property prices and credit ranking alternatively second and third. This is consistent with these two variables being slow-moving variables. Second, for most countries, the relative order of output, inflation and the policy rate, is consistent with the order adopted on theoretical grounds in most workhorse VAR that includes these three variables. The only surprising feature of these orderings is that stock prices are ordered before inflation and the policy rate. Because stock prices react immediately to changes in inflation or monetary policy, it seems plausible to attribute the contemporaneous correlation between stock prices and inflation or the policy rate to a reaction of these two last variables to equity rather than the opposite. This counter-intuitive ordering of stock prices could arise if, for instance, stock prices react in anticipation to monetary and inflation shocks, that are considered as unexpected in the VAR (in the sense of not captured by its systematic component), but that are in practice anticipated by equity

Table 3.3: P-values for Shapiro-Wilk test (H_0 : the sample is normally distributed)

	gdp	cpi	ST.rate	equity	credit	property
US	0.096	0 ***	0 ***	0.047 *	0.014 *	0.664
UK	0.882	0.123	0 ***	0.079	0.171	0.545
Japan	0 ***	0.017 *	0 ***	0.883	0.211	0.801
Germany	0.49	0.711	0.002 **	0.915	0.656	0.239
Belgium	0.121	0.255	0.616	0.041 *	0.007 **	0.821
Canada	0.141	0.383	0.028 *	0 ***	0.306	0.185
Netherlands	0 ***	0.488	0.09	0.649	0.92	0 ***
France	0.718	0.001 ***	0 ***	0.158	0.623	0.043 *
Italy	0.034 *	0.121	0.011 *	0.752	0.576	0.404
Denmark	0.735	0.906	0 ***	0.168	0.301	0.805
Sweden	0.009 **	0.07	0.001 ***	0.257	0.012 *	0.241
Spain	0 ***	0 ***	0 ***	0.081	0 ***	0.805
Australia	0.189	0.174	0 ***	0.081	0.387	0.691
Norway	0.141	0.301	0 ***	0.001 ***	0.034 *	0.212
Switzerland	0.207	0.619	0.221	0.006 **	0.48	0.81
New.Zealand	0.082	0.299	0.019 *	0.755	0.389	0.052
Ireland	0 ***	0.024 *	0 ***	0.39	0 ***	0.495

*p<0.05; **p<0.01; ***p<0.001

Table 3.4: Recursive ordering implied by the ICA algorithm

	1	2	3	4	5	6
US	credit	gdp	property	equity	cpi	ST.rate
UK	gdp	credit	property	equity	cpi	ST.rate
Japan	property	gdp	credit	equity	cpi	ST.rate
Germany	property	gdp	credit	equity	ST.rate	cpi
Belgium	gdp	property	credit	equity	cpi	ST.rate
Canada	gdp	credit	property	equity	ST.rate	cpi
Netherlands	gdp	credit	property	equity	ST.rate	cpi
France	property	gdp	credit	equity	cpi	ST.rate
Italy	gdp	property	credit	equity	cpi	ST.rate
Denmark	gdp	credit	property	equity	cpi	ST.rate
Sweden	gdp	property	credit	equity	cpi	ST.rate
Spain	gdp	credit	property	equity	cpi	ST.rate
Australia	gdp	property	credit	equity	ST.rate	cpi
Norway	gdp	property	credit	equity	ST.rate	cpi
Switzerland	gdp	credit	property	equity	cpi	ST.rate
New.Zealand	credit	gdp	property	equity	cpi	ST.rate
Ireland	gdp	property	equity	credit	cpi	ST.rate

market agents. The recent adoption of forward guidance by modern central banks may for instance create better anticipation of future policy rates, that is not accounted for by the model over the full historical sample. In that case, the fast-moving reaction of stock prices to these shocks would happen before the shocks and therefore the model would fail to attribute these shocks to the contemporaneous value of equity, thereby classifying equity as a slower-moving variable than inflation and the policy rate. These limitations notwithstanding, it is encouraging that a broadly similar causal ordering is generated across countries. The slight differences may reflect different financial market structures and prevailing financial frictions. These differences may for instance be related to heterogeneity in the relative importance of bank loans versus market-based loans, of fixed versus moving interest rates, of debt versus equity, or of external versus internal finance. The maturity profile of firms, as well as the sectoral composition, may play a role in such differences. Importantly, our results suggest that the typical ordering assumed in the literature, whereby financial variables are systematically ordered below macroeconomic variables, is rejected in our dataset. One notable difference is that financial variables should be included above inflation and the policy rate.

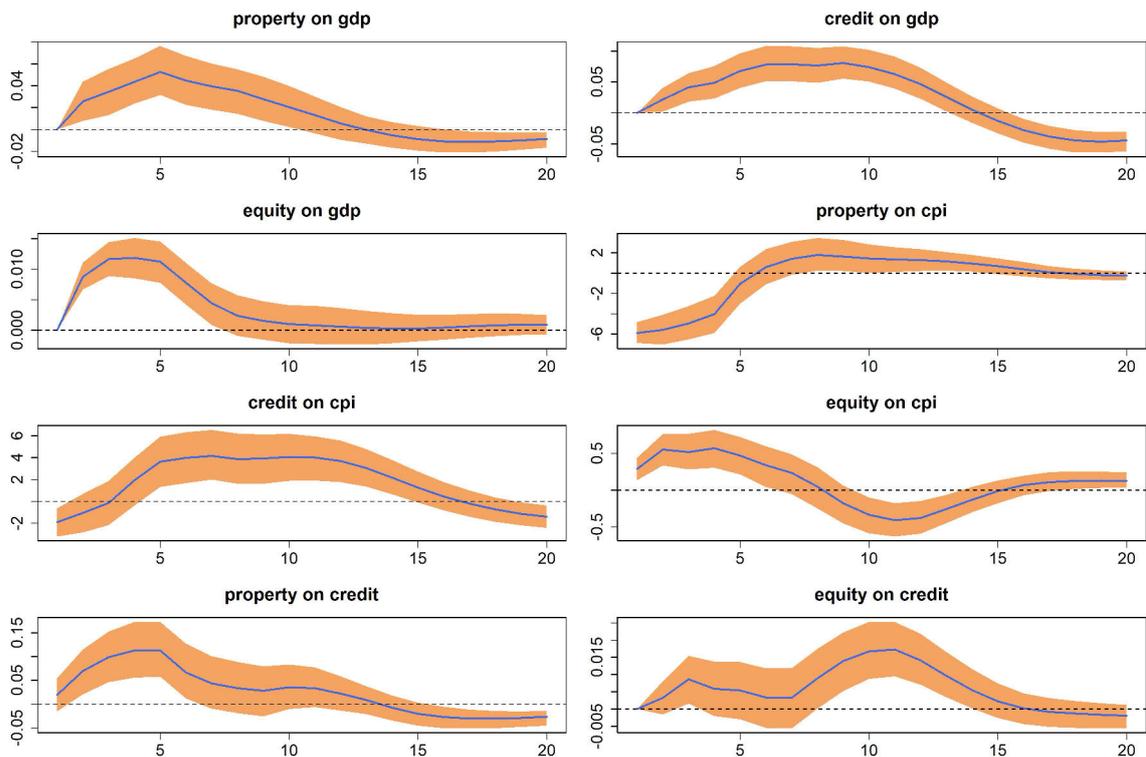


Figure 3.1: IRF for the Pooled estimator

The relative homogeneity in the recursive orders warrants the application of panel techniques with a unique order for all countries, without incurring a major loss of information. The ordering for the Panel VAR estimation is: output, property, credit, equity, inflation and the policy rate. We first estimate the pooled model. The normalized estimated impulse response functions (IRFs) are depicted in [Figure 3.1](#). The confidence intervals are calculated via bootstrapping at the 5% and the 95% levels. The IRFs for the Mean-Group estimator

are provided in the [Appendix](#).

Our results suggest that after a financial shock, output increases between 8 and 15 quarters and then goes back to steady state. These findings are in line with those obtained in SVAR identified with sign restrictions. The impact of credit shocks is more long-lasting than shocks to property or stock prices, consistent with the prominent role of credit in Business Cycle fluctuations documented in the empirical literature. A potential caveat regarding the impact of stock price shocks on output is that our empirical framework is not capable of separating causal and forward-looking relationships. A positive effect of stock prices on output could instead arise because forward-looking agents anticipate that future economic conditions will affect future stock prices. The elasticity of output to property price shocks is higher than the elasticity of output to stock price shocks. This may bear upon the fact that housing wealth represents a large proportion of household wealth in developed countries and plays a prominent role for the borrowing capacity of households and small-businesses alike. The fact that a positive shock on asset prices increases credit in the short-run is consistent with financial accelerator mechanisms at play. Moreover, credit reacts more strongly to property prices than to stock prices, thereby confirming that the real impact of asset prices manifests first and foremost via changes in the former. Another crucial feature of our results is that the impact of a financial shock on inflation is ambiguous. In particular, inflation tends to drop right after a property price shock. This is reminiscent of the years preceding the GFC, when consumer inflation remained subdued despite the emergence of a housing bubble in most developed countries. Although the model is theoretically not able to disentangle demand and supply shocks⁹, the fact that output and inflation move in opposite direction for property shocks suggests that property price shocks behave more like a supply shock, while credit shocks behave more like a demand shock. This interpretation should be read with care however.

We finally report the Forecast Error Variance Decomposition (FEVD). By construction, in the case of SVAR identified with short-term restrictions, the contribution of the exogenous component of the variable ordered first tend to be very high. This statistical artifact bears upon the fact that the variance of omitted variables correlated with output, as well as the variance of shocks to variables ordered after output that are correlated with output shocks, will be attributed to output. Therefore, the forecast error variance associated to financial shocks should be understood as the residual of innovations of financial variables, once their correlation with contemporaneous shocks of output, is accounted for. Consequently, the FEVD only provides a lower bound estimate of the contribution of financial shocks to output fluctuations. We find that overall, financial shocks account for at least 15% of the forecast error variance of output after two years. The derivation and the results of the FEVD analysis can be found in the [Appendix](#).

⁹The identification of demand and supply shocks at the aggregate level is, in principle, possible, with a different identification scheme, such as long-run restrictions, or sign restrictions.

3.5 Conclusion

In this chapter, we have shown that the recursive ordering usually assumed in VAR models that identify financial shocks with short-term restrictions is rejected by the data. Under the sole assumption of contemporaneous acyclicity of the Data Generating Process, we provide evidence that financial shocks contribute significantly to Business Cycle fluctuations. The relationship between financial factors and economic activity could instead be non-causal, as financial variables may embed information about future economic prospects. The next chapter explores this possibility.

Appendix B

Appendix - Chapter 3

B.1 IRF for the Mean-Group estimator

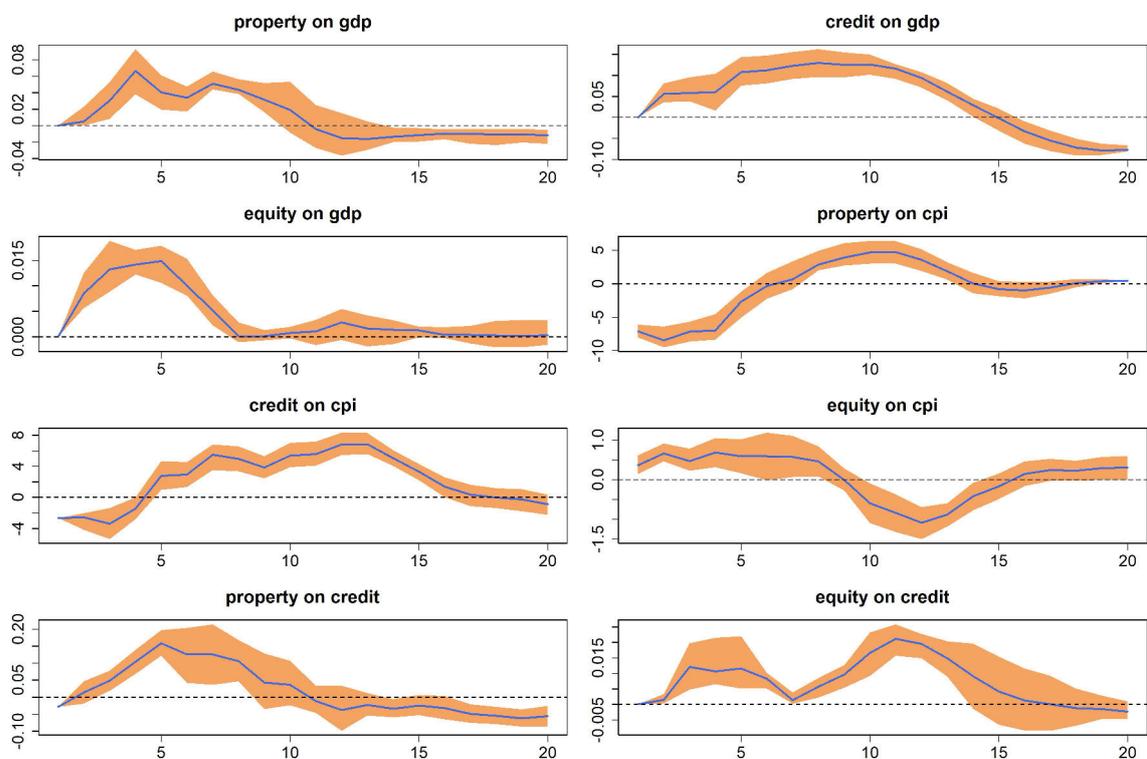


Figure B.1: IRF for the Mean-Group estimator

B.2 Transformed variables

We plot the variables in stationary form, except for inflation and credit, which are plotted along with their local mean (in red) before de-meaning.

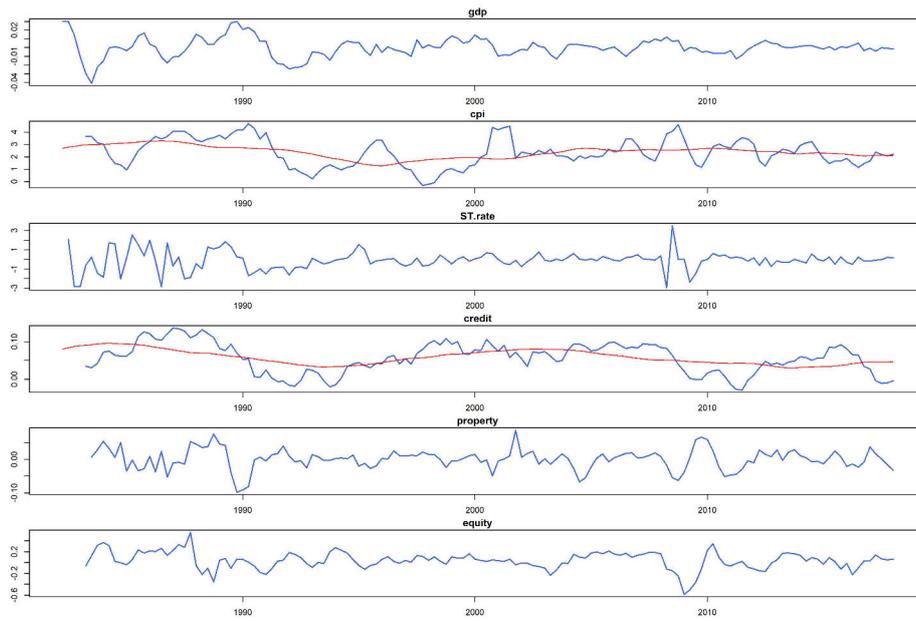


Figure B.2: Australia

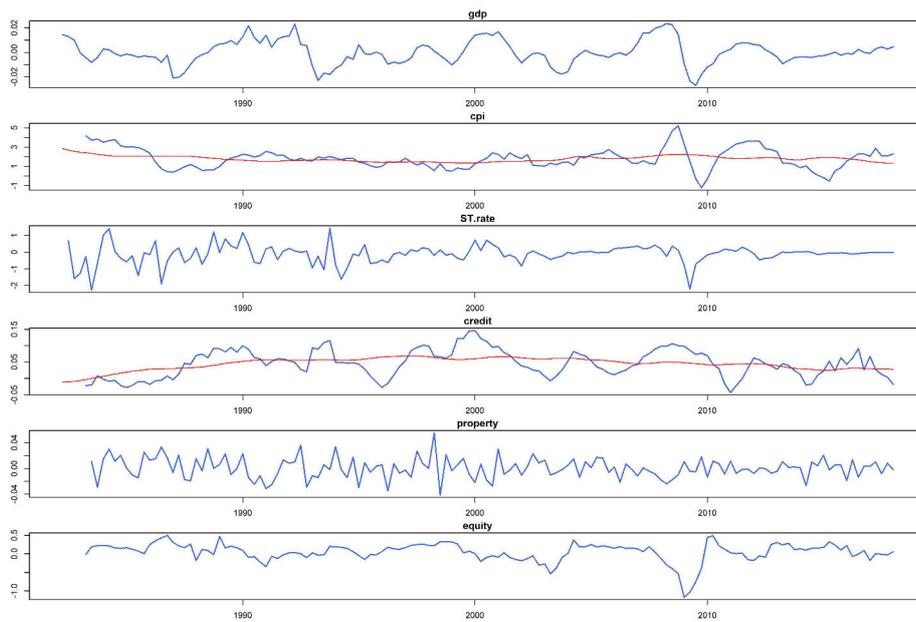


Figure B.3: Belgium

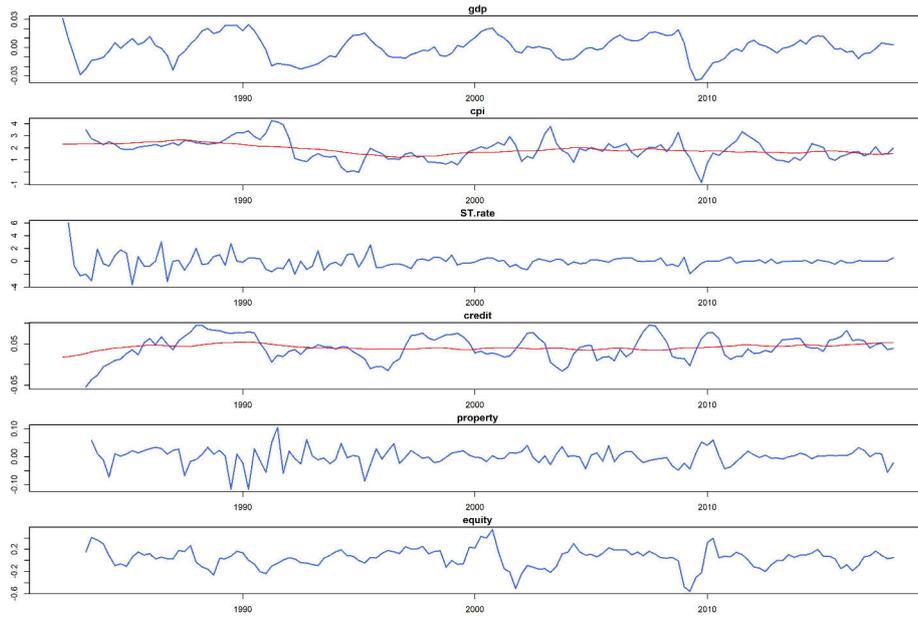


Figure B.4: Canada

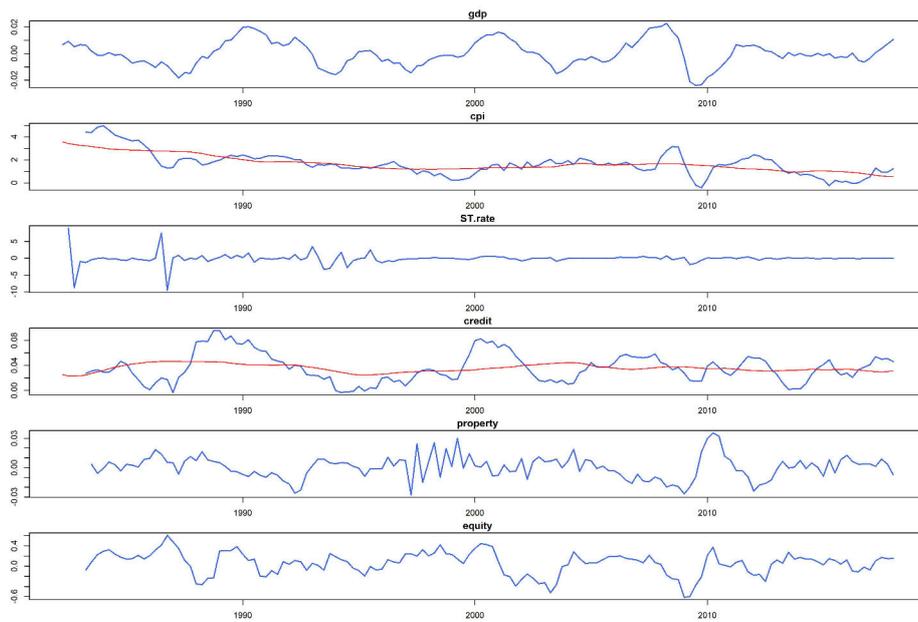


Figure B.5: France

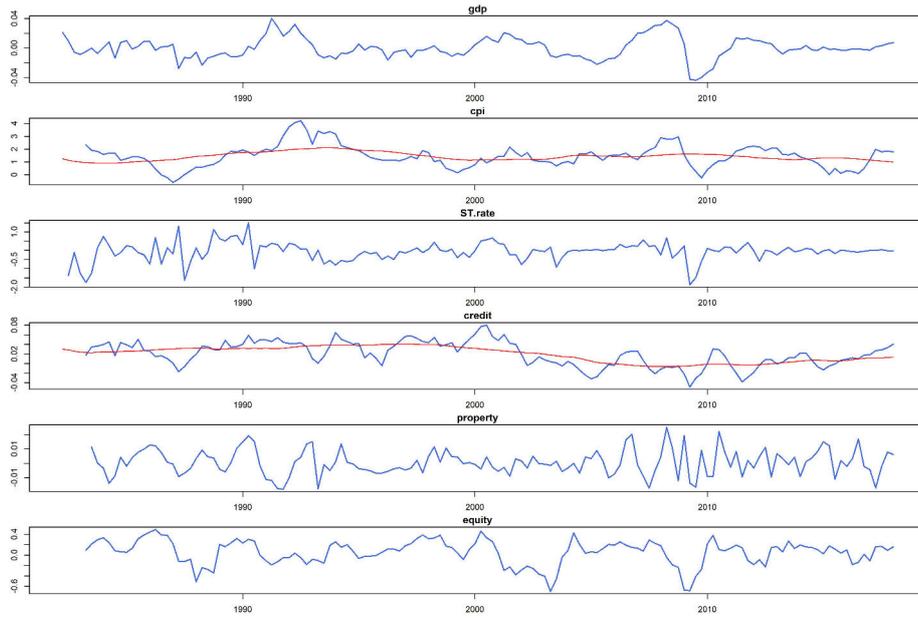


Figure B.6: Germany

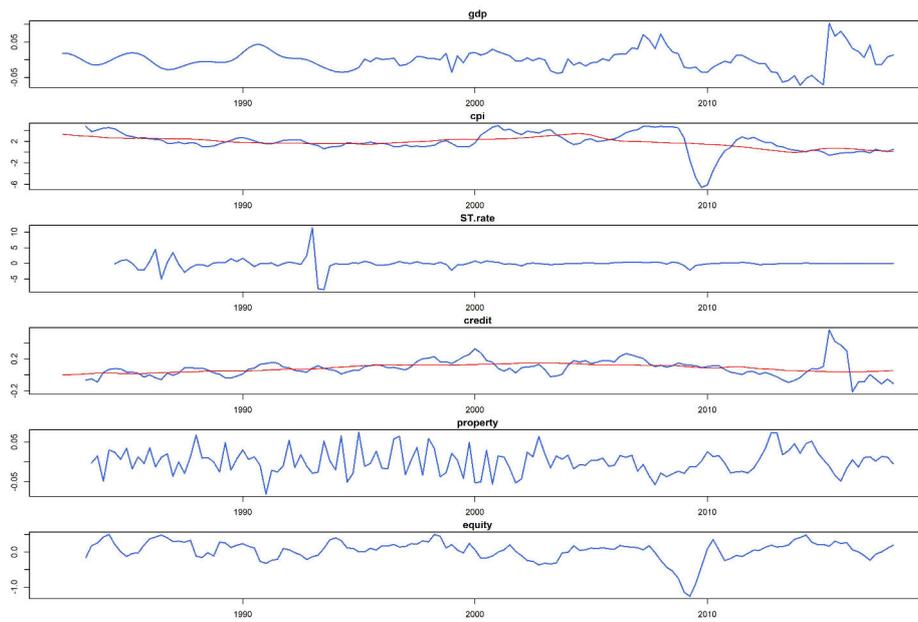


Figure B.7: Ireland

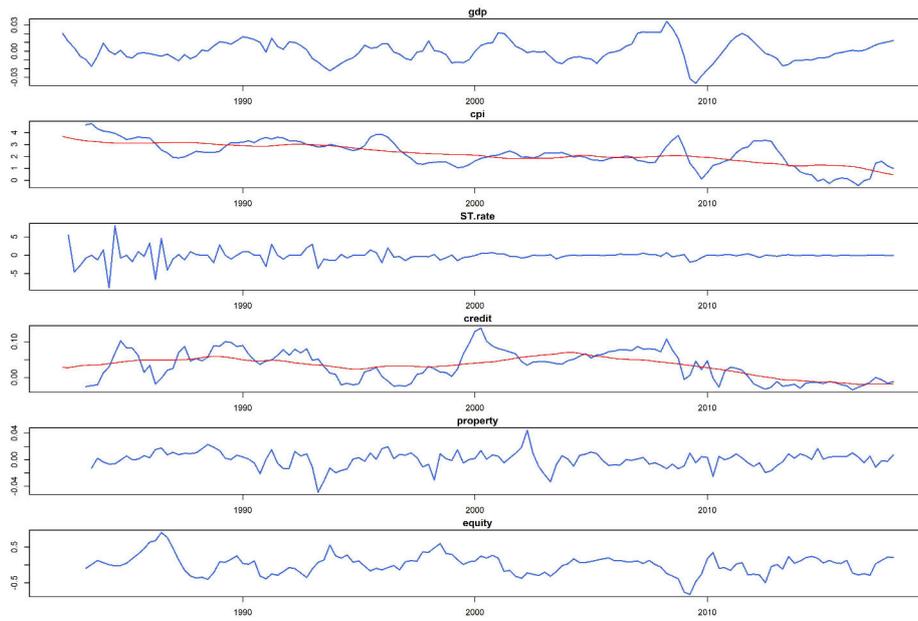


Figure B.8: Italy

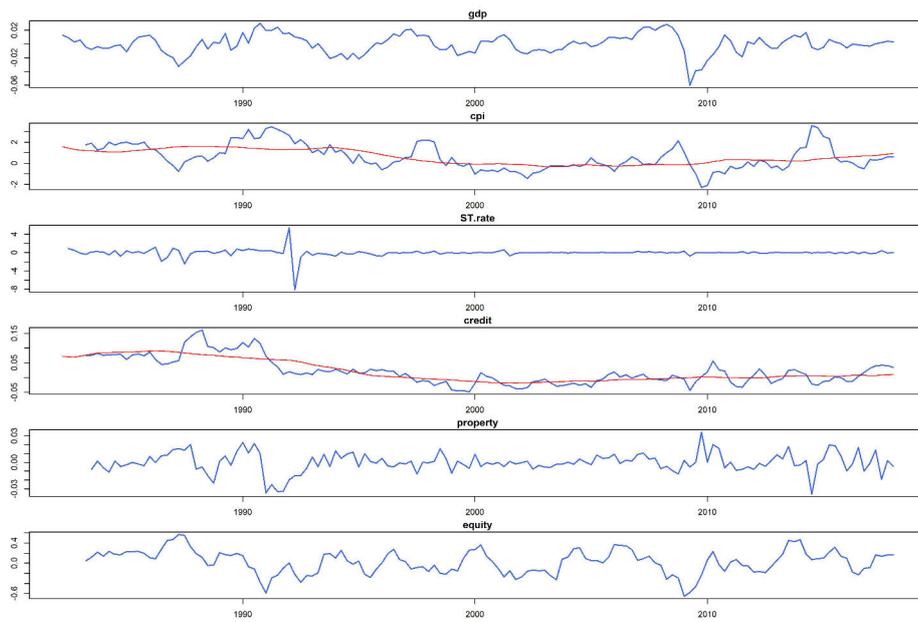


Figure B.9: Japan

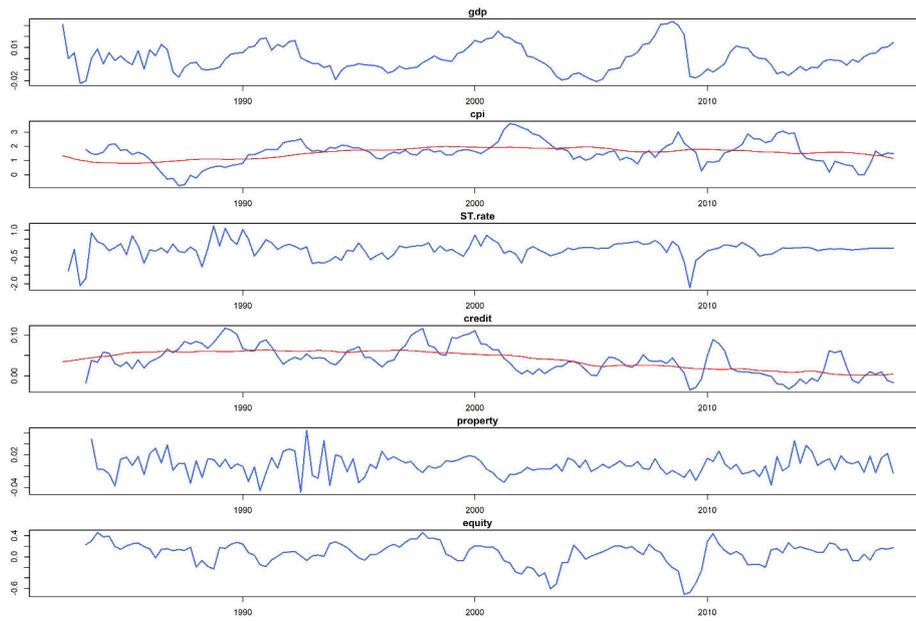


Figure B.10: Netherlands

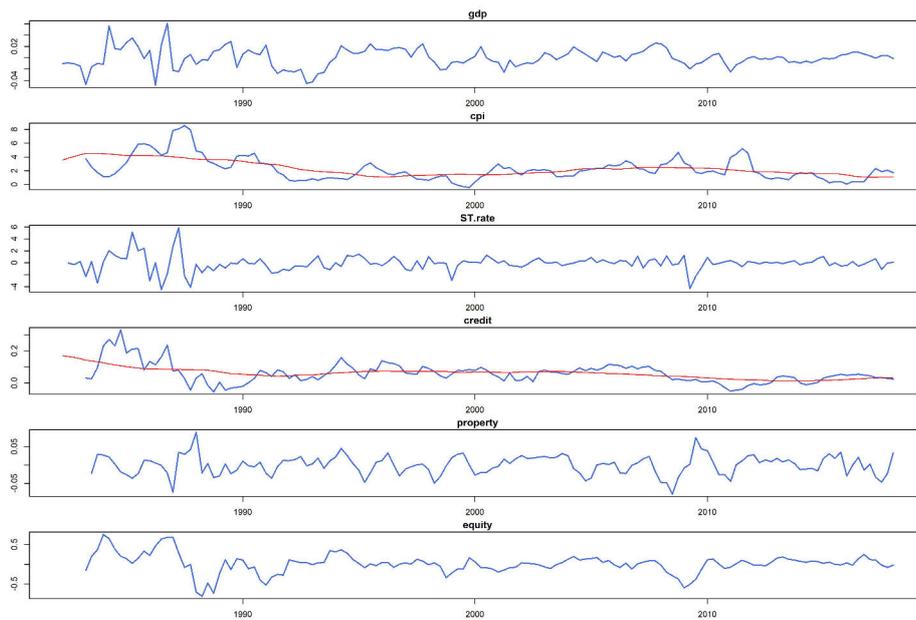


Figure B.11: New Zealand

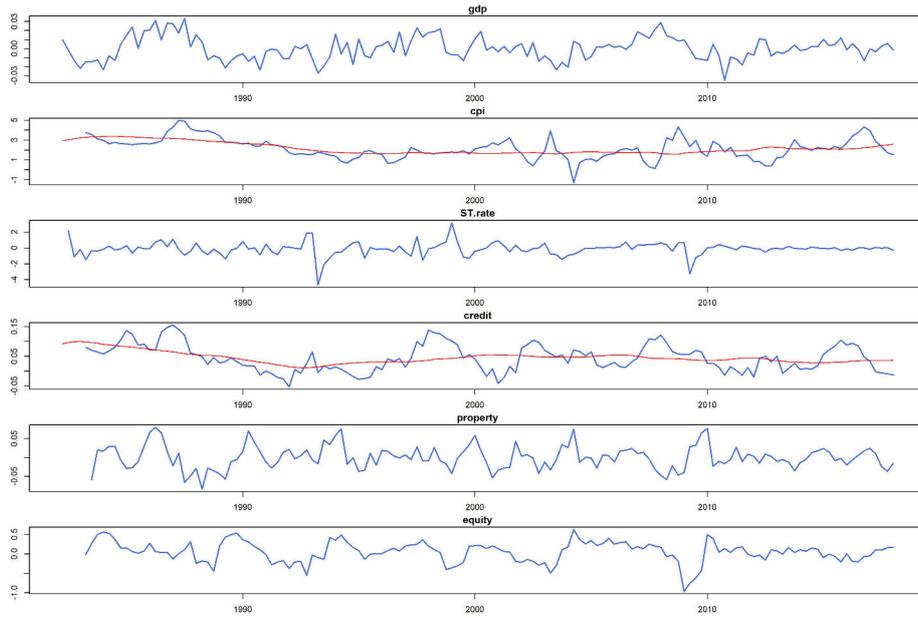


Figure B.12: Norway

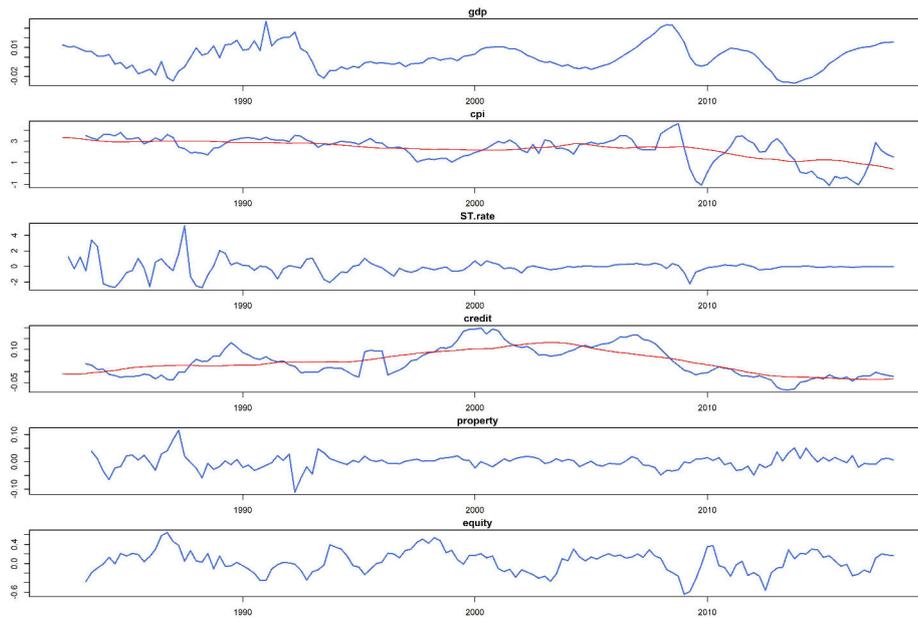


Figure B.13: Spain

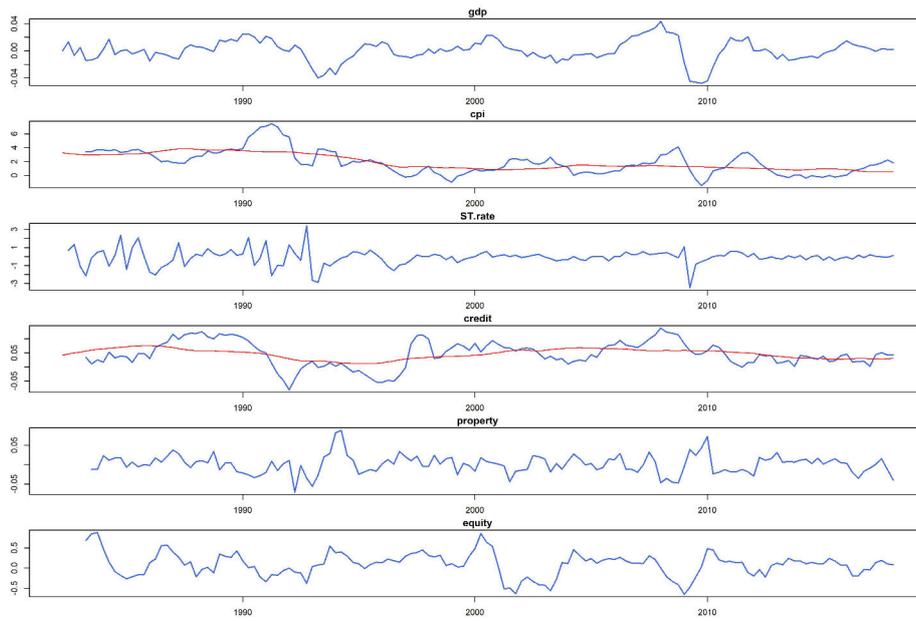


Figure B.14: Sweden

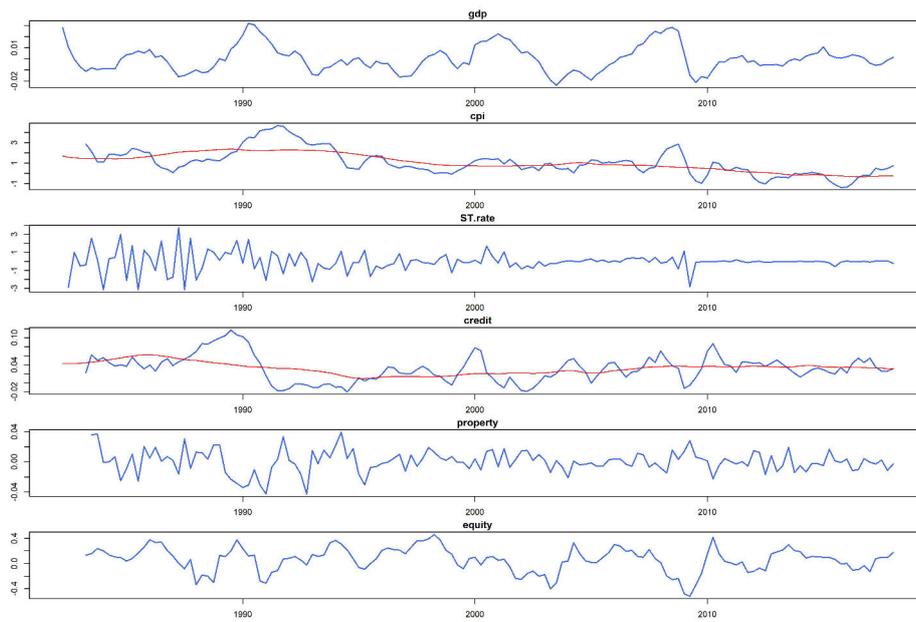


Figure B.15: Switzerland

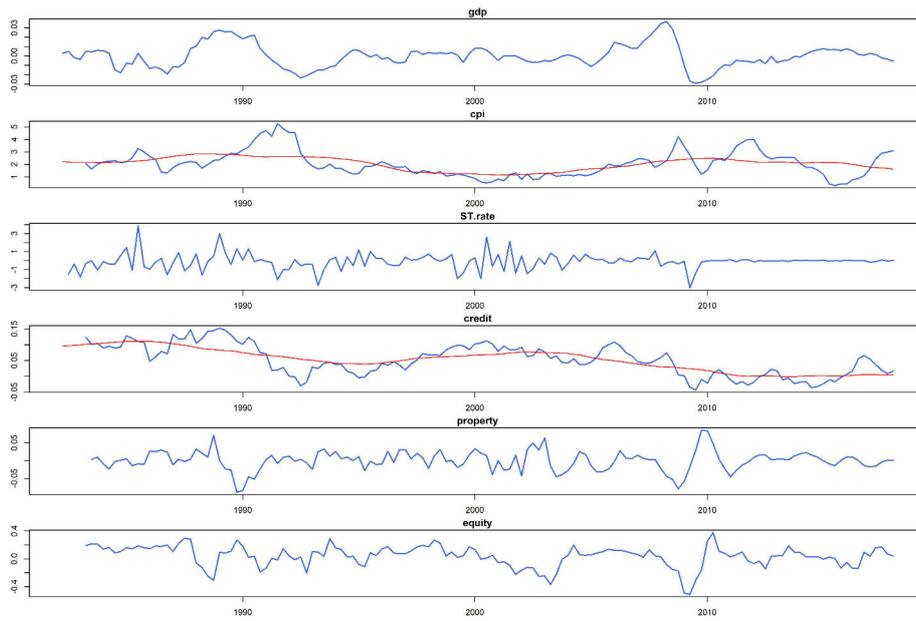


Figure B.16: United Kingdom

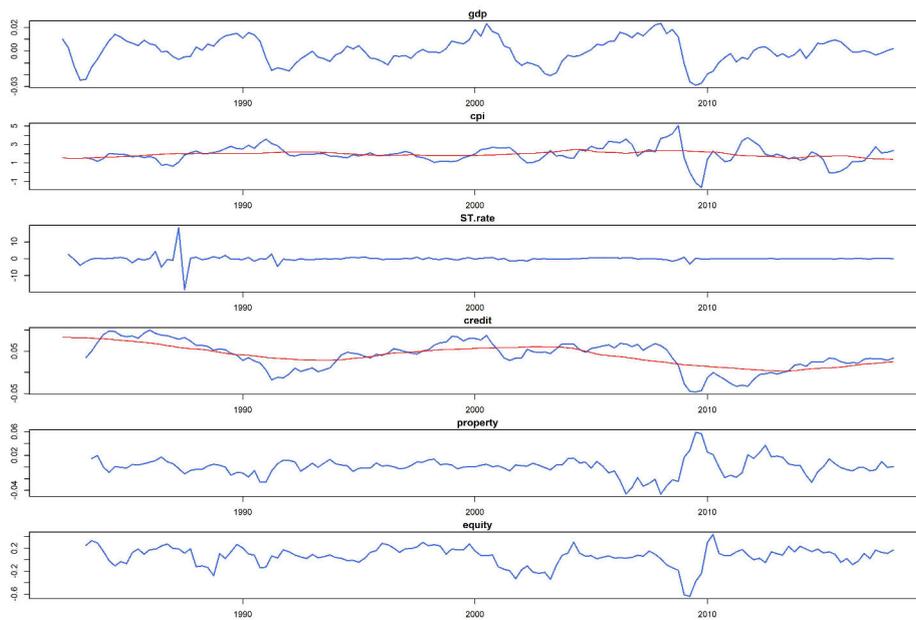


Figure B.17: United States

B.3 Causal order

The following table displays the contemporaneous causal structures estimated by the Independent Component Analysis for country-specific models. The variable on the top contemporaneously causes the variable on the left:

Table B.1: Causal structure Lag 0 (1/3)

US						
	gdp	cpi	ST.rate	equity	credit	property
gdp	0	0	0	0	0	0
cpi	0	0	0	1.219	0	-40.303
ST.rate	0	0	0	0	0	0
equity	0	0	0	0	0	0
credit	1.06	0	0	0	0	0
property	0	0	0	0	0	0

UK						
	gdp	cpi	ST.rate	equity	credit	property
gdp	0	0	0	0	0	0
cpi	0	0	0	0	0	-6.201
ST.rate	0	0	0	0	0	0
equity	0	0	0	0	0	0
credit	0	0	0	0	0	0
property	0	0	0	0	0	0

New Zealand						
	gdp	cpi	ST.rate	equity	credit	property
gdp	0	0	0	0	0.28	0
cpi	0	0	0	0	0	0
ST.rate	0	0	0	0	0	0
equity	0	0	0	0	0	0
credit	0	0	0	0	0	0
property	0	0	0	0	0	0

Japan						
	gdp	cpi	ST.rate	equity	credit	property
gdp	0	0	0	0	0	0
cpi	0	0	0	1.069	0	-37.935
ST.rate	0	0	0	0	0	0
equity	0	0	0	0	0	0
credit	0.926	0	0	0	0	0
property	0	0	0	0	0	0

Germany						
	gdp	cpi	ST.rate	equity	credit	property
gdp	0	0	0	0	0	0
cpi	0	0	0	0	0	-37.186
ST.rate	0	0	0	0	0	0
equity	0	0	0	0	0	0
credit	0.64	0	0	0	0	0
property	0	0	0	0	0	0

Belgium						
	gdp	cpi	ST.rate	equity	credit	property
gdp	0	0	0	0	0	0
cpi	32.381	0	0	0	0	0
ST.rate	25.7	0	0	0	0	0
equity	0	0	0	0	0	0
credit	0	0	0	0	0	0
property	0	0	0	0	0	0

Table B.2: Causal structure Lag 0 (2/3)

Canada						
	gdp	cpi	ST.rate	equity	credit	property
gdp	0	0	0	0	0	0
cpi	0	0	0	0	-12.409	0
ST.rate	0	0	0	0	0	0
equity	0	0	0	0	0	0
credit	0.98	0	0	0	0	0
property	0	0	0	0	0	0

Netherlands						
	gdp	cpi	ST.rate	equity	credit	property
gdp	0	0	0	0	0	0
cpi	0	0	0	0	0	-12.633
ST.rate	0	0	0	0	0	0
equity	0	0	0	0	0	0
credit	0	0	0	0	0	0
property	0	0	0	0	0	0

France						
	gdp	cpi	ST.rate	equity	credit	property
gdp	0	0	0	0	0	0
cpi	0	0	0	0	0	0
ST.rate	0	0	0	0	58.632	0
equity	0	0	0	0	0	0
credit	0	0	0	0	0	0
property	0	0	0	0	0	0

Italy						
	gdp	cpi	ST.rate	equity	credit	property
gdp	0	0	0	0	0	0
cpi	0	0	0	0	0	0
ST.rate	0	0	0	0	0	0
equity	0	0	0	0	0	0
credit	0	0	0	0	0	0
property	0	0	0	0	0	0

Denmark						
	gdp	cpi	ST.rate	equity	credit	property
gdp	0	0	0	0	0	0
cpi	0	0	0	0	0	0
ST.rate	0	0	0	0	0	0
equity	0	0	0	0	0	0
credit	0	0	0	0	0	0
property	0	0	0	0	0	0

Sweden						
	gdp	cpi	ST.rate	equity	credit	property
gdp	0	0	0	0	0	0
cpi	0	0	0	0	0	0
ST.rate	0	0	0	0	0	0
equity	0	0	0	0	0	0
credit	0.952	0	0	0	0	0
property	0	0	0	0	0	0

Table B.3: Causal structure Lag 0 (3/3)

Spain						
	gdp	cpi	ST.rate	equity	credit	property
gdp	0	0	0	0	0	0
cpi	0	0	0	0	0	0
ST.rate	0	0	0	0	0	0
equity	9.923	0	0	0	0	0
credit	0	0	0	0	0	0
property	0	0	0	0	0	0

Australia						
	gdp	cpi	ST.rate	equity	credit	property
gdp	0	0	0	0	0	0
cpi	0	0	0	0	0	-11.692
ST.rate	0	0	0	0	0	0
equity	0	0	0	0	0	0
credit	1.021	0	0	0	0	0
property	0	0	0	0	0	0

Norway						
	gdp	cpi	ST.rate	equity	credit	property
gdp	0	0	0	0	0.325	0
cpi	0	0	0	0	0	0
ST.rate	0	0	0	0	0	0
equity	0	0	0	0	0	0
credit	0	0	0	0	0	0
property	0	0	0	0	0	0

Switzerland						
	gdp	cpi	ST.rate	equity	credit	property
gdp	0	0	0	0	0	0
cpi	0	0	0	0	0	0
ST.rate	0	0	0	0	0	0
equity	0	0	0	0	0	0
credit	0.69	0	0	0	0	0
property	0	0	0	0	0	0

Ireland						
	gdp	cpi	ST.rate	equity	credit	property
gdp	0	0	0	0	0	0
cpi	0	0	0	0	0	0
ST.rate	0	0	0	0	0	0
equity	0	0	0	0	0	0
credit	1.903	0	0	0	0	0
property	0	0	0	0	0	0

B.4 Forecast Error Variance Decomposition

The Forecast Error Variance Decomposition (FEVD) is based on the proportion of the variability of the errors in forecasting each variables at time $t + s$ based on information available at time t that is due to variability in the structural shocks between times t and $t + s$. We first start with the reduced-form Moving Average representation:

$$y_{t+s} = A_0 + u_{t+s} + \Psi_1 u_{t+s-1} + \dots$$

The best linear forecast of y_{t+s} based on information available at time t is:

$$\hat{y}_{t+s|t} = \mu + \Psi_s u_t + \Psi_{s+1} u_{t-1} + \dots$$

and the forecast error is:

$$y_{t+s} - \hat{y}_{t+s|t} = u_{t+s} + \Psi_1 u_{t+s-1} + \dots + \Psi_{s-1} u_{t+1}$$

Rewriting the forecast error in terms of the structural shocks:

$$\begin{aligned} y_{t+s} - \hat{y}_{t+s|t} &= B_0^{-1} \epsilon_{t+s} + \Psi_1 B_0^{-1} \epsilon_{t+s-1} + \dots + \Psi_{s-1} B_0^{-1} \epsilon_{t+1} \\ &= \Theta_0 \epsilon_{t+s} + \Theta_1 \epsilon_{t+s-1} + \dots + \Theta_{s-1} \epsilon_{t+1} \end{aligned}$$

Focusing on the first equation:

$$\begin{aligned} y_{1t+s} - \hat{y}_{1,t+s|t} &= \theta_{1,1}(0) \epsilon_{1,t+s} + \dots + \theta_{1,1}(s-1) \epsilon_{1,t+1} \\ &+ \theta_{1,2}(0) \epsilon_{1,t+s} + \dots + \theta_{1,2}(s-1) \epsilon_{1,t+1} \\ &\vdots \\ &+ \theta_{1,K}(0) \epsilon_{1,t+s} + \dots + \theta_{1,K}(s-1) \epsilon_{1,t+1} \end{aligned}$$

Since the structural shocks are *i.i.d.*, the variance of the forecast error may be decomposed as:

$$\begin{aligned} \text{Var}(y_{t+s} - \hat{y}_{t+s|t}) &= \sigma_1^2(s) \\ &= \sigma_1^2 \left(\theta_{1,1}(0)^2 + \dots + \theta_{1,1}(s-1)^2 \right) \\ &+ \sigma_1^2 \left(\theta_{1,2}(0)^2 + \dots + \theta_{1,2}(s-1)^2 \right) \\ &\vdots \\ &+ \sigma_1^2 \left(\theta_{1,K}(0)^2 + \dots + \theta_{1,K}(s-1)^2 \right) \end{aligned}$$

The FEVD for $y_{i,t+s}$ is the proportion of $\sigma_i^2(s)$ due to shocks in ϵ_j , for all $j \leq K$, that is:

$$\text{FEVD}_{i,j}(s) = \frac{\sigma_j^2 \left(\theta_{i,j}(0)^2 + \dots + \theta_{i,j}(s-1)^2 \right)}{\sigma_i^2(s)}$$

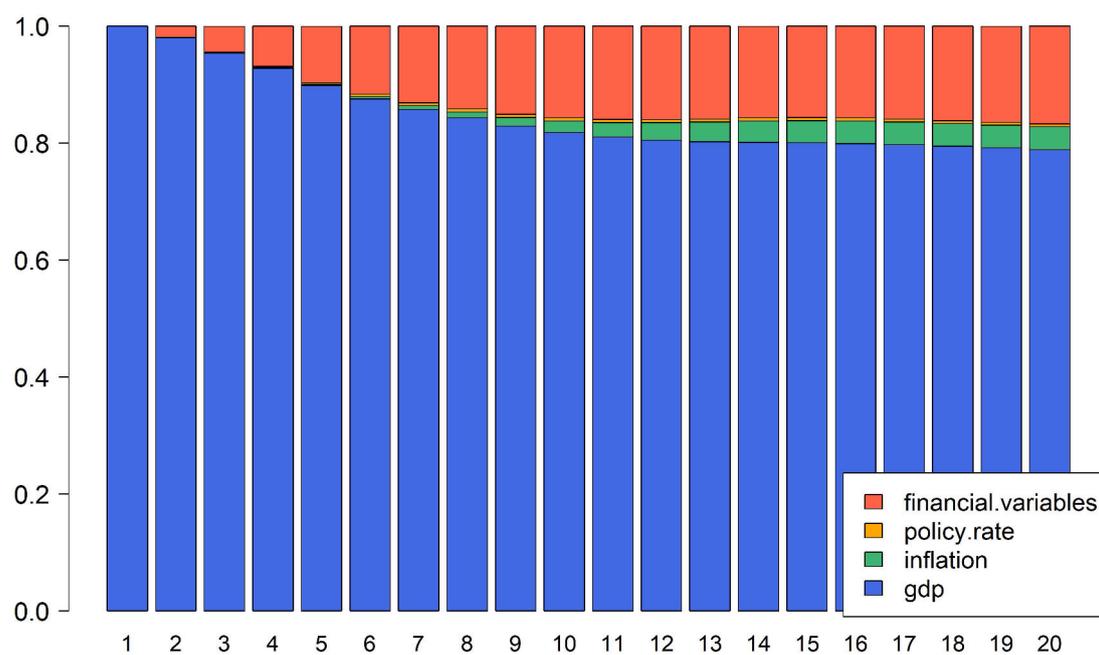


Figure B.18: Forecast Error Variance Decomposition

Chapter 4

Failing to Predict with Financial Variables: Defending the Case of the Usual Suspect

4.1 Introduction

The previous chapter focused on the causal relationship between financial factors and macroeconomic outcomes. If the Efficient Market Hypothesis holds, even in its weakest form, this relationship could also be non-causal, as financial variables ought to contain information about investors' beliefs concerning the near-term path of the economy. First, forecasting economic activity is a crucial input for fiscal and monetary policy. Second, professional forecasters play a crucial role in forming the macroeconomic expectations of the broader public. The idea of using asset prices as leading indicators of the Business Cycle arose mainly in the 1970s and 1980s when forecasting models based on monetary aggregates or the Phillips curve ceased to be effective. Since then, a long line of studies has investigated the information content of financial variables for future economic conditions. Alas, a crucial feature of this literature is that the forecasting power of financial variables tends to be highly unstable and to vanish after some times, especially around turning points or in times of heightened uncertainty, where the cost of an inappropriate policy mix is higher. This is all the more surprising that the structural changes of the 1980s should have increased the signal-to-noise ratio of financial variables. Theoretically, lower inflation and a clarification of central banks' procedures¹ should lower the risk premium associated with aggregate uncertainty and entail a purer signal from financial variables.

One reason for the lack of efficiency of forecasting models that include financial variables could be that these variables are not reliable predictors of economic activity. An alternative possibility, however, is that standard forecasting models should be blamed instead. Imposing constraints on the underlying Data Generating Process may not be suited to capture the gist of financial factors, by nature multi-faceted and episodic. For instance, the linearity

¹As reported by [Cook and Hahn \[1989\]](#), the Fed's lack of clarity produced such poor expectations of funds target changes that these changes were nearly equivalent to surprises.

assumption made in most standard econometric models is almost always an approximation. In that case, non-parametric Machine Learning algorithms, that are relatively agnostic about the Data Generating Process, should outperform standard forecasting models.

This chapter uses a battery of models to assess if the instability of forecasting models with financial variables stems from the predictors themselves or from inappropriate modeling devices. To this end, we compare the performances of parametric and non-parametric models for forecasting the U.S. Industrial Production from one to six months ahead, with a set of twelve financial variables. To investigate whether these relationships have changed over time and to allow for a shift in regime around the Great Moderation, we perform the exercise on two different samples, 1962-1985 and 1986-2017. Importantly, we do not aim to perform a horse race between forecasting models, but only to disentangle the potential gains from different modeling features, such as predictor selection, non-linearity, or data reduction techniques.

4.2 The predictive power of financial variables

The premise that asset prices contain useful information to predict output has strong theoretical underpinnings. First, financial factors may actively affect economic activity through neoclassical mechanisms, such as the interest rate channel for consumption and investment expenditures, wealth effects, or non-neoclassical channels arising from financial frictions². Second, asset prices are forward-looking by nature as they incorporate all the information of market participants about the underlying real asset, a feature also known as the Efficient Market Hypothesis. Theoretically, the price of an asset today indeed depends on the expectation of the asset's future payoffs, which are linked to future economic developments and the way this payoff interacts with the stochastic discount factor, itself being related to agents' preferences and the state of the economy. Moreover, if economic agents take allocation and real decisions based on the information conveyed by asset prices, changes in asset prices can have real consequences. A more technical reason that makes asset prices useful predictors of the Business Cycle is that marked-to-market financial variables quote at high-frequency. Therefore, unlike economic "hard data", which are backward-looking, measured at low-frequency and with potentially large measurement errors, financial variables are "fast-moving" inputs for short-term forecasting.

The most widely used financial variable for predicting economic activity is the term spread, or premium, between long-term and short-term interest rates ([Estrella and Hardouvelis \[1991\]](#); [Estrella and Mishkin \[1997\]](#); [Bernard and Gerlach \[1998\]](#); [Estrella \[2005\]](#); [Ang et al. \[2006\]](#); [Stock and Watson \[1989\]](#)). The Expectation Hypothesis of the term structure of interest rates claims that long-term rates are purely determined by current and future expected short-term rates. Hence, long-term rates should reflect investors' beliefs in the evolution of future growth and inflation. A decreasing term spread, also known as yield curve flattening, thereby tend to signal lower future economic activity. The type of flattening matters to understand why

²See the introductory chapter for a review of transmission mechanisms of financial factors to the real sector.

it could be a useful predictor of economic activity. A “bear-flattening”, stemming from a decrease in long-term rates, reflects expectations of low future short-term rates related to the central bank’s response to a bleak economic outlook and low inflation expectations. A “bull-flattening” instead arises from the short-end of the yield curve as the result of tighter monetary policy. While in the former case the relationship with future macroeconomic outcomes is likely to be non-causal, it reflects the adverse effects of higher short-term rates on consumption and investment spending in the latter case. Additionally, a flatter yield curve also makes maturity transformation less profitable for financial intermediaries, which in turn dampens loan supply. For all of these reasons, an inversion of the yield curve has been found to be a harbinger of recessions. All the twelve recessions that have occurred in the U.S. in the post-1950 were preceded by an inversion of the yield curve. The only false signal, in 1966, was followed by an increase in the unemployment rate. [Harvey \[1989\]](#) showed that although the in-sample forecasting power of the yield curve is good, out-of-sample results are more mixed. [Ng and Wright \[2013\]](#) and [Stock and Watson \[2003\]](#) show that term spreads were good predictors of economic activity until the 1980s, when their relevance started to fade. [Bordo and Haubrich \[2004\]](#) provide evidence that the predictive power of the yield curve depends on the monetary regime and tends to vanish when the latter becomes more credible.

Corporate spreads, i.e. spreads on private sector securities over comparable maturity Treasuries, have also been found to anticipate Business Cycle phases. Corporate bond spreads usually serve as a proxy for the External Finance Premium faced by credit-constrained firms, which is defined as the gap between the cost of capital raised from external sources and the cost of capital raised internally. An increase in bond spreads thereby signals a departure from the Modigliani-Miller paradigm of frictionless financial markets. Such an increase has been found to cause large and persistent contractions in economic activity ([Gilchrist et al. \[2009b\]](#)), either because it reflects tighter financial conditions for firms, or higher expectations of default. [Gertler and Lown \[1999\]](#) investigate the forecasting power of corporate bond spreads and show that they tend to outperform the term spread, the paper-bill spread and the Fed Funds rate over the recent period. [Ng \[2014\]](#) instead finds that the term spread and credit spreads have independent and complementary explanatory power.

Stock prices, because they reflect the expected present discounted value of future earnings, are linked to nominal growth expectations. The relationship between stock prices and economic activity can also be causal, via wealth and financial accelerator mechanisms or the Tobins’s Q theory of investment. In practice, however, the in-sample predictive power of equity prices has been found to be rather weak ([Fama \[1981\]](#); [Harvey \[1989\]](#)), both for regression ([Stock and Watson \[1989\]](#)) and classification models ([Estrella and Mishkin \[1998\]](#)).

The wide range of candidate variables notwithstanding, a crucial feature of the literature is therefore that the predictive power of asset prices is inherently unstable, especially in out-of-sample exercises ([Stock and Watson \[2003\]](#)). As claimed by [Stock and Watson \[2003\]](#)³ no single asset price can be lastingly used as a reliable predictor of economic activity. In

³“It appears that instability of predictive relations based on asset prices is the norm.”

addition, when controlling for lags of the endogenous variable, linear models including asset prices often fail to beat simple autoregressive models. The inclusion of multiple financial variables have been found to outperform individual financial variables (Hatzius et al. [2010]), but is still subject to significant instability.

Several potential factors may explain the erratic nature of the relationship between financial variables and future macroeconomic outcomes. First, financial and informational frictions may blur the fundamental signal provided by asset prices. In that case, financial prices will reflect imperfectly aggregate expectations about future economic conditions. For instance, economic agents taking part in the price discovery process on financial markets may diverge about future states of the world. If the dispersion around the mean is too important, prices may reflect an average view that is uninformative about future economic conditions. This is possible even when beliefs are on average unbiased, if, for instance, pessimistic agents are constrained in their ability to short financial assets (Miller [1977]). The financial micro-structure also matters. A market that is mostly driven by non-fundamental agents, performing “smart beta” strategies, such as trend-following or mean-reversion techniques, or relying on algorithmic trading strategies, will be of little help to forecast economic conditions. By the same token, liquidity conditions may affect financial prices and explain the bulk of changes in prices when liquidity conditions deteriorate, potentially dwarfing the fundamental component of asset prices. The less liquid the market, the more marginal buyers and sellers will unduly affect prices. Price departures from fundamentals can also arise if agents are influenced by “irrational waves” (Minsky [1982]; Kindleberger [1989]), whereby bouts of euphoria or herding make the market bubbly, reflecting expectations on future price rather than views on fundamentals. Blanchard and Watson [1982] even allow for “rational bubbles”, by relaxing the transversality condition of the Present Value Model. Finally, not all movements on financial markets are relevant for economic activity. For instance, some U.S. corporates have recently engaged in a vast program of share buybacks⁴, which mechanically boosts earnings-per-share by cutting back the number of outstanding shares. In that case, an increase in stock prices implies, *ceteris paribus*, lower current investment and thereby lower future growth, contrary to what theory indicates.

Second, the relationship between asset prices and economic variables may be state-dependent. For instance, because stock prices are sensitive to short-term interest rates, sound job market statistics can be detrimental for stock prices towards the end of the Business Cycle, when the central bank keeps a close watch on inflationary pressures. By the same token, as recalled by Chari et al. [2008], movements in interest rate spreads may be informative about the cost of borrowing during normal times, but not during financial stress episodes, when flight-to-quality portfolio rebalancing may depress interest rates on safe assets.

Third, an additional reason why financial variables are not stable predictors of economic activity is related to non-stationarity induced by changes in the distribution of financial vari-

⁴In the U.S., share buybacks amount to 3% of the market capitalization per year over the last decade.

ables over time⁵. For instance, if the central bank or macroprudential regulators exert some control over a financial variable, or use it as a leading indicator in order to stabilize the economy, this will mechanically lower its correlation with economic outcomes. Moreover, even if the underlying economic processes were stationary, heterogeneity in the observed time series can arise from technical changes. In the case of quantity variables, these changes may be caused by a modification of the measurement process, including coverage and definitions. For price variables, changes in the market structure may alter the data generating process of the time series.

A final reason, which does not preclude the three previous ones, bears upon the possibility that the modeling frameworks used to extract the information content of financial variables is not suited to account for the non-linear and elusive nature of macro-financial linkages. This is the line of thought that we set forth in this chapter by testing whether considering flexible modeling tools helps to extract the economic content of financial variables.

4.3 The data

Because we are interested in assessing the predictive power of financial variables over a long time span and across several phases of the Business Cycle, our analysis goes from 1962 to 2017 and includes seven Business Cycles according to the NBER dating procedure. It is widely acknowledged that the volatility of output growth and inflation experienced a major structural break in the mid-1980s (Kim and Nelson [1999]; Blanchard and Simon [2001]; Chauvet and Potter [2001]). This phenomenon, referred to as the Great Moderation, is partly related to significant changes in the conduct of monetary policy in industrialized countries, whereby restoring price stability became the overarching goal of central bankers (Bernanke and Mihov [1998]; Sims and Zha [2006]). Although the Great Moderation has made forecasting easier (Chauvet and Potter [2013]), changes in the conduct of monetary policy over time may account for the reduced informativeness of financial variables associated to monetary policy (Gertler and Lown [1999]). In order to account for this structural break, we consider separately two different periods, 1962-1984 and 1985-2017. Regarding the Global Financial Crisis, it is well-known that forecast errors increased dramatically during the crisis precisely because models had been trained on periods of low volatility (Chauvet and Potter [2013]). However, because we are interested in models that are robust to high and low volatility episodes, the second period goes uninterrupted from 1985 to 2017.

As mentioned earlier, the set of potential financial variables likely to convey information about future economic prospects is vast. Instead of considering the forecasting power of financial variables individually, we include several variables likely to be complementary along the Business Cycle. Because our forecasting models feature variable selection, data reduction or Bayesian estimation, we are to some extent safeguarded from the curse of dimensionality. However, because cross correlation of regressors in large datasets might result in inaccurate

⁵As opposed to non-stationarity related to unit roots.

forecasts (Boivin and Ng [2006]), we try to avoid variables that are too correlated. Conceptually, this is done by avoiding redundancy in the theoretical mechanisms underlying macro-financial linkages. We first consider several interest rate variables, which, except for the policy rate, enter the model in spread to reduce colinearity. The term spread between 10-Year and 3-Month Treasury bonds (T10YmT3M) captures the slope of the yield curve and is an early-warning indicator of recessionary episodes. The spread between 3-Month commercial paper⁶ and 3-Month Treasury bonds (COMPAPmT3M) and the spread between Moody’s Aaa corporate bond and 10-Year Treasury bonds (AAAm10Y) reflect financing conditions of firms on the unsecured short-term debt market and the long-term debt market respectively. We also include the spread between firms rated Baa⁷ and Aaa (BAAmAAA) as a proxy of the External Financial Premium. The choice of this specific rating is consistent with Gilchrist et al. [2009b], which argue that much of the predictive power of bond spreads for economic activity is embedded in securities issued by intermediate-risk firms rather than high-risk firms. We also include the volume of business (BUSLOANS) and consumer loans (CONSMOTLOANS and TOTCONSLOANS) which potentially capture financial frictions not necessarily accounted for by interest rates, such as credit rationing. Real Estate loans (REALLN) are also included to account for financial accelerator mechanisms. The inclusion of stock prices (S&P 500) is self-explanatory given the prominence of the stock market for the U.S. economy. We also consider the Price Earning ratio (S&P PE ratio), which indicates whether stock prices are expensive and control for large departure of stock prices from their equilibrium value. The Chicago Board Options Exchange S&P 100 Volatility Index (VXO) reflects investors’ expectations about short-term (30-day) volatility in the stock market and is a good proxy for financial stress. Finally, we include a measure of money supply, Money Zero Maturity (MZM)⁸, which is considered as a relevant proxy for money readily available for spending and has been found to exhibit a more stable relationship with economic activity than other measures of money supply (Teles and Zhou [2005]). All the selected financial variables are provided by the Federal Reserve Bank of St. Louis.

As far as economic activity is concerned, GDP stand out as a natural proxy. However, we prefer to work with monthly data in order to improve statistical inference. We therefore use the Industrial Production Index instead, which is a monthly counterpart of real GDP provided by the Federal Reserve. Unlike GDP, which encompasses both durable and nondurable goods within personal consumption expenditures, fixed investment, change in private inventories and net exports, Industrial Production focuses on changes in the volume of value added in manufacturing, mining and electric and gas utilities⁹. However, GDP growth and Industrial Production growth tend to diverge because most of the growth in U.S. GDP goods arises in the retail and wholesale trade industries rather than manufacturing industries. Additionally, the volatility of quarterly U.S. Industrial Production tends to be twice that of U.S. GDP (Andreou et al. [2000]). This discrepancy is not so problematic if we assume that financial

⁶Commercial paper typically serves for the financing of accounts payable and inventories.

⁷Baa is the first tranche of credit rating that may possess speculative characteristics.

⁸Money Zero Maturity is computed as M2 (physical currency + checking and saving accounts) – time deposit + money market funds. A notable caveat is that MZM does not include repurchase agreements.

⁹In the U.S., Industrial Production represents about 15% of total GDP.

factors mostly affect economic activity via capital-intensive industries. Nonetheless, it is not clear-cut whether the results of this chapter would hold if GDP was used instead.

Table 4.1: Data transformation

Code	Variable	Transformation
INDPRO	Industrial Production Index	First difference of logarithm
BUSLOANS	Commercial and Industrial Loans	Second difference of logarithm
MZM	MZM Money Stock	Second difference of logarithm
REALLN	Real Estate Loans at All Commercial Banks	Second difference of logarithm
CONSMOTLOANS	Consumer Motor Vehicle Loans Outstanding	Second difference of logarithm
TOTCONSLOANS	Total Consumer Loans and Leases Outstanding	Second difference of logarithm
FEDFUNDS	Effective Federal Funds Rate	First difference
S&P 500	S&P Common Stock Price Index: Composite	First difference of logarithm
S&P PE ratio	S&P Composite Common Stock: Price-Earnings Ratio	First difference of logarithm
VXO	CBOE S&P 100 Volatility Index	Level
T10YmT3M	10-Year Treasury Minus 3-Month Treasury	Level
AAAm10Y	Aaa Corporate Bond Minus 10-Year Treasury	Level
BAAmAAA	Baa Minus Aaa Corporate Bond	Level
COMPAPmT3M	3-Month commercial paper Minus 3-Month Treasury	Level

Each variable is transformed to achieve stationarity over the two sub-samples. Outliers¹⁰ are removed and replaced by the median. Because Machine Learning algorithms can be very sensitive to differences in scale, the data is standardized between 0 and 1. [Table 4.1](#) shows the selected variables as well as the transformation implemented to achieve stationarity. Stationarity is then tested with the Augmented Dickey-Fuller test ([Table 4.2](#)). We plot the transformed variables ([Figure 4.1](#)) as well as the unconditional correlation table on the full sample ([Figure 4.2](#)).

¹⁰An outlier is defined as an observation that deviates from the sample median by more than ten interquartile ranges.

Table 4.2: P-values for ADF test (H_0 : presence of unit root)

	1962-1985	1986-2017
INDPRO	0.01 ***	0.01 ***
BUSLOANS	0.023 **	0.038 **
MZM	0.01 ***	0.01 ***
REALLN	0.251	0.054 *
CONSMOTLOANS	0.01 ***	0.01 ***
TOTCONSLOANS	0.037 **	0.01 ***
FEDFUNDS	0.01 ***	0.01 ***
S.P.500	0.01 ***	0.01 ***
S.P.PE.ratio	0.01 ***	0.01 ***
VXO	0.021 **	0.055 *
T10YmT3M	0.268	0.026 **
AAAm10Y	0.069 *	0.044 **
BAAmAAA	0.055 *	0.01 ***
COMPAPmT3M	0.05 **	0.026 **

*p<0.01; **p<0.05; ***p<0.1

The forecasting exercise is carried out in pseudo real-time, which means that the explanatory variables should obey to the three prominent conditions of quality, timeliness and coherence (McKenzie and Park [2006]). Financial variables comply with these requirements as they are not revised and released without measurement errors. Finally, as requested by Stock and Watson [1996], financial variables have “consistent historical definitions” and are corrected for potential issues of changing data availability and definitions.

Contrary to financial variables, Industrial Production, which also enters the model as a regressor in lagged form, is subject to significant revisions after the first estimate. In that case, a crucial issue regarding the choice between preliminary and revised data is whether the revision is “news” or “noise”, in the terminology of Mankiw and Shapiro [1986]. If statistical agencies producing the initial estimate process all available information efficiently, the revision will be “news” and will be uncorrelated with the preliminary estimate, but correlated with the final value. If, on the contrary, statistical agencies estimate early releases by adding “noise” to the final estimate that is progressively reduced across subsequent revisions, the revision will only be correlated with the early estimate.

Using preliminary data would mimic more realistically the exercise of the real-time forecaster, while there is a risk of using “too much information” with revised data (Rudebusch [1998]). In the case of “noise” revisions, however, forecast produced with preliminary data will mechanically be inefficient and therefore the forecast will not be rational¹¹. Estimating the forecasting model with revised data should therefore improve the signal-to-noise ratio of our model and therefore yield better forecast. Cole [1969] for instance show that the forecast error is typically twice as bigger in the case of preliminary data relative to revised data. Revised

¹¹A forecast is said to be rational if it is unbiased (not systematic prediction error) and efficient, in the sense that all the available information is used, in line with the Rational Expectation theory.

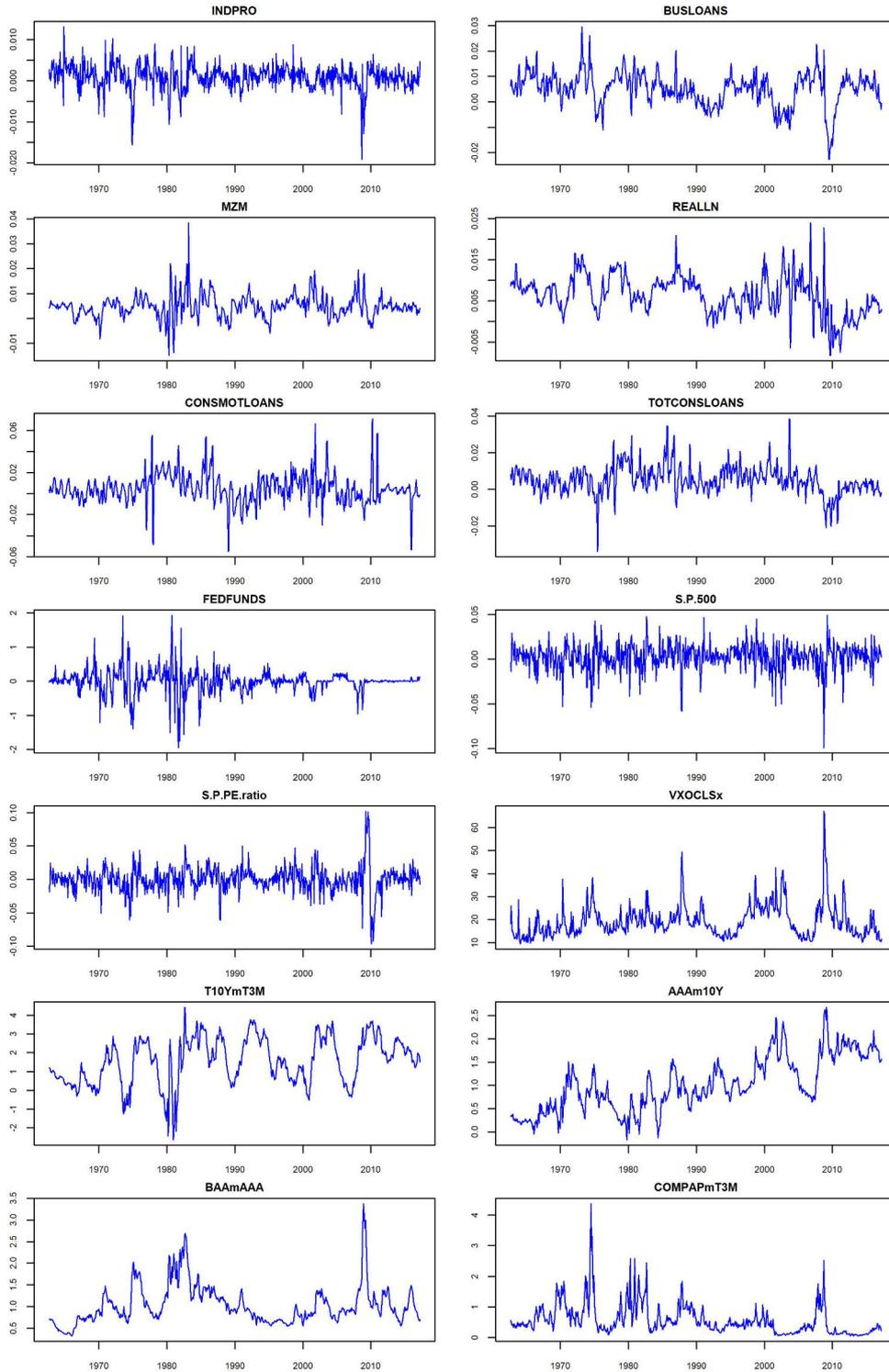


Figure 4.1: Transformed variables

data also offers the advantage of dealing with changes in definition. Moreover, the nature of the revision process also has crucial consequences for the model estimation. In the case of “noise” revisions, the model coefficients will be estimated consistently even with revised data (Bernanke and Mihov [1998]), albeit with potentially greater variance. In the case of “news”, on the contrary, the error-in-variables model suggests that the residuals will be correlated with one of the regressors and therefore that estimated coefficient will be biased and

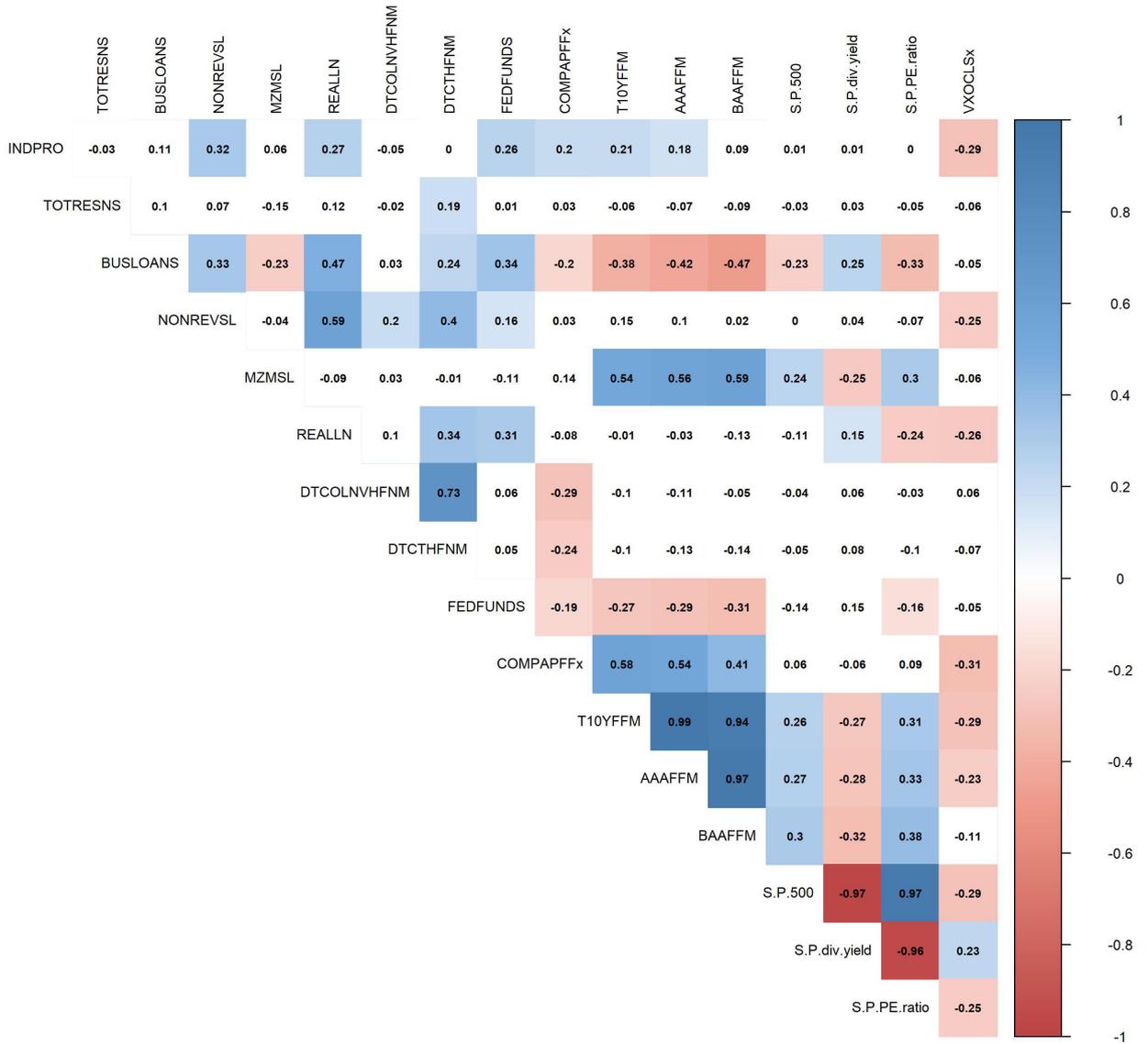


Figure 4.2: Correlation between transformed variables

inconsistent (Rudebusch [1998]). Therefore, if revisions of Industrial Production are “news”, we should use provisional data. On the contrary, if they are “noise”, we should use revised data. While empirical evidence suggests that GDP revisions do contain a substantial amount of “news” (Diebold et al. [1987], Mankiw and Shapiro [1986]), the literature is more silent about Industrial Production revisions. We therefore investigate the property of Industrial Production revisions. Let $R_t = y_t^F - y_t^P$ be the revision between the preliminary estimate y_t^P and the final estimate y_t^F of Industrial Production for period t . Should the correlation between R_t and y_t^P (y_t^F) be statistically different from zero, the revision is noise (news). The correlation between revisions and the successive vintages of Industrial Production are shown

in [Table 4.3](#). For the two periods, we are not able to claim whether the revision process is “noise” or “news”. Intuitively, when it comes to forecasting, the cost related to endogeneity, would the revision be “news”, is lower than the cost in terms of forecast efficiency, would the revision be “noise”. We therefore decide to use the latest available vintage of Industrial Production.

Table 4.3: Correlation between Industrial Production growth rate and revisions

1963-1985				
	First estimate	Second estimate	Third estimate	Final estimate
First to Second Revision	-0.023	0.238 ***	0.263 ***	0.201 ***
Second to Third Revision	0.02	0.06	0.275 ***	0.183 ***
Third to Final Revision	0.409 ***	0.439 ***	0.469 ***	-0.071
First to Final Revision	0.388 ***	0.285 ***	0.219 ***	-0.227 ***
1986-2016				
	First estimate	Second estimate	Third estimate	Final estimate
First to Second Revision	0.053	0.413 ***	0.424 ***	0.272 ***
Second to Third Revision	-0.035	0.003	0.244 ***	0.112 **
Third to Final Revision	0.271 ***	0.341 ***	0.383 ***	-0.264 ***
First to Final Revision	0.249 ***	0.107 **	0.053	-0.448 ***

*p<0.01; **p<0.05; ***p<0.1

4.4 The forecasting models

4.4.1 The general model

Regarding the choice of the forecasting model, the first step is to make a choice between a structural and a reduced-form model, a parametric and a non-parametric model and whether the model should be linear or not. Structural models, such as Dynamic Stochastic General Equilibrium (DSGE) or Structural VAR models offer the advantage of not being vulnerable to the Lucas Critique¹². However, most of the time with these models, forecasting only comes as a by-product. The alternative is to use reduced-form models, where only part of the relationship between variables is modeled. Such models include Dynamic Factor Models, Bayesian VARs, Markov-Switching models, or Mixed-Frequency models. Comparison exercises of the forecasting power of structural and reduced-form models are rather mixed. For instance, while DSGE models with nominal rigidities outperform VAR models for forecasting economic activity ([Smets and Wouters \[2005\]](#)), they are less effective around turning points and in periods of high macroeconomic volatility ([Del Negro and Schorfheide \[2012\]](#)). More generally, a somewhat counter-intuitive result in the literature is that causal models do not necessarily yield better forecast than non-causal models ([Clements and Hendry \[1999\]](#); [Allen](#)

¹²The Lucas critique ([Lucas \[1976\]](#)), states that policy measures that are based on observed empirical relationships alter the data generating process under which these relationships were observed. For forecasting, the Lucas critique implies that non-structural models are doomed to loose relevance after some time owing to self-fulfilling expectations of agents reacting to them.

and Fildes [2001]; Fildes and Stekler [2002]). Chauvet and Potter [2013] show that structural models do not have more forecasting power than univariate time series models. It is equally disconcerting that complexity does not ensure higher forecasting capacity. Kolasa and Rubaszek [2015] find that accounting for demand and supply financial frictions in DSGE models does not improve the accuracy of point forecast in normal times and even lowers the quality of density forecast. Likewise, while more complex techniques, such as models with time-varying parameters, should intuitively lead to better forecasts, they are rarely able to beat simple univariate models (Faust and Wright [2013]). Consequently, naive models, such as random walks, tend to result in better forecasts (Fildes and Ord [2002]) owing to their robustness to sources of instability such as structural breaks.

Based on the premise that forecasting errors tend to increase around Business Cycle turning points (Chauvet and Potter [2013]) and that most financial series exhibit substantial mean-shifts (Andreou et al. [2000]), several studies test whether non-linear forecasting models perform better than linear models. Chauvet and Hamilton [2006] find that the univariate Markov-Switching model of Hamilton [1989] and the Dynamic Factor Markov-Switching model of Chauvet [1998] are useful tools for forecasting U.S. Business Cycles in real time. When including asset prices to forecast U.S. Industrial Production, Jaditz et al. [1998] show that non-linear forecasts also fare better than linear models. Ferrara et al. [2015] show, however, that nonlinear models rarely improve forecasts relative to their linear counterpart, even during the GFC.

Overall, the key takeaway from the vast literature on forecasting economic activity is that there is no such thing as the “best model” at all times and in all states of the world. Chauvet and Potter [2013] show that no model performs better both in normal times and around turning points and therefore advocate for using specific models for each phase of the Business Cycle. An alternative is to pool forecasts from different models (Timmermann [2006]; Clark and McCracken [2010]; Kuzin et al. [2013]). The rationale is that combining several models helps to mitigate the impact of model misspecifications, arising from variable selection and model specification, and to benefit from diversification when forecasting errors are not perfectly correlated across models. Given the inherent instability of forecasting models, a strand of the literature even argues that judgmental forecasts should be preferred to forecasting models insofar as they perform better than DSGE or BVAR models (Del Negro and Schorfheide [2013]; Wieland and Wolters [2011]).

Unlike the issues mentioned herein, the choice between parametric and non-parametric techniques for forecasting has received scarce attention in the empirical literature. Non-parametric models offer the advantage that no assumptions about the type of relationship between input variables and the response variable is needed. Machine Learning is a set of non-parametric data-driven techniques (although there exist parametric Machine Learning techniques), mostly used for pattern recognition. Supervised Learning, which is a subset of Machine Learning that maps an input to an output, can be used for classification purposes, like detecting turning points or for prediction. There are several reasons to believe that Ma-

chine Learning algorithms are suited for the extraction of the information content of financial variables. First, they are capable of handling large datasets of potentially correlated data, for instance by performing jointly the selection of variables and the estimation. Second, they are more flexible than standard econometric models and allow to model more complex interactions between the variables. Notwithstanding extensive work on the forecasting performances of Machine Learning algorithms, their application to macroeconomic research has hitherto confined to the detection of crises. [Ng \[2014\]](#) and [Berge \[2015\]](#) use the Boosting algorithm to perform model selection for the prediction of recessions. [Ghosh and Ghosh \[2003\]](#) and [Frankel and Wei \[2004\]](#) apply Regression Tree techniques to select leading indicators of crises. [Nag and Mitra \[1999\]](#) try to detect exchange rate crises in emerging countries via Artificial Neural Networks.

In this chapter, we consider a large battery of models that each provide some sort of comparative advantage with respect to the double constraint of dealing with a large dataset and potentially non-linear dynamics. The Bayesian VAR (BVAR) and the Factor Augmented Distributed Lag (FADL) models keep the assumption of linearity but are able, each in their own way, to deal with a large dataset. As regards Machine Learning algorithms, we first use Regularized Regression and Bayesian Structural Time Series (BSTS) methods to test whether automatic feature selection techniques are capable of enhancing the signal extraction. Then the linearity assumption is relaxed with Regression Trees and Artificial Neural Networks, which offer two different alternatives to the modeling of non-linear dynamics.

An important issue in forecasting exercises is the choice between the direct approach and the iterated approach. Iterated forecast consists in estimating a model based on a one step-ahead criterion and then iterating upon the model at the expected horizon. Direct forecast, on the contrary, consists in fitting the parameters so as to minimize directly the desired multi-step function of the in-sample prediction errors. For the autoregressive model, as shown by [Bhansali \[1996\]](#), [Ing \[2003\]](#) and [Bhansali \[1997\]](#), the best method will depend on the degree of misspecification of the model. If the one-step ahead model is misspecified, owing for instance to a smaller number of lags than in the true Data Generating Process, the iterated method is efficient but biased and the direct approach outperform the iterated approach. More generally, consider a VAR(p) process:

$$Y_t = c + A_1 Y_{t-1} + \dots + A_p Y_{t-p} + \varepsilon_t$$

Any VAR(p) process can be rewritten as a VAR(1) process:

$$\begin{pmatrix} Y_t \\ Y_{t-1} \\ \vdots \\ Y_{t-p-1} \\ Y_{t-p} \end{pmatrix} = \begin{pmatrix} c \\ 0 \\ \vdots \\ \vdots \\ 0 \end{pmatrix} + \begin{pmatrix} A_1 & A_2 & \dots & A_{p-1} & A_p \\ I_n & 0 & \dots & 0 & 0 \\ 0 & I_n & \ddots & 0 & 0 \\ 0 & & \ddots & & \vdots \\ 0 & \dots & \dots & I_n & 0 \end{pmatrix} \begin{pmatrix} Y_{t-1} \\ Y_{t-2} \\ \vdots \\ Y_{t-p-2} \\ Y_{t-p-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_t \\ 0 \\ \vdots \\ \vdots \\ 0 \end{pmatrix}$$

In addition, a VAR(1) for variable x_t with a non-zero intercept can be re-written as a VAR(1)

with no-intercept by considering instead $X_t = [1 \quad x_t]'$, which yields:

$$X_t = \Psi X_{t-1} + \mathcal{E}_t$$

The h -period ahead forecast of X_t from period T is given by:

$$X_{T+h} = \Psi^h X_t + \sum_{i=0}^{h-1} \Psi^i \mathcal{E}_{T+h-i}$$

The 1-step estimator is defined by:

$$\hat{\Psi} = \arg \min_{\Psi} \left| \sum_{t=1}^T (X_t - \Psi X_{t-1})(X_t - \Psi X_{t-1})' \right|$$

The iterated h -step forecast is therefore given by $\hat{X}_{T+h} = \hat{\Psi}^h X_T$.

The h -step direct forecast is defined by the least-squares projection:

$$\tilde{\Psi}_h = \arg \min_{\Psi_h} \left| \sum_{t=1}^T (X_t - \Psi_h X_{t-h})(X_t - \Psi_h X_{t-h})' \right|$$

The direct h -step forecast is therefore given by

$$\tilde{X}_{T+h} = \tilde{\Psi}_h X_T$$

The relative forecast accuracy therefore depends on the deviation of $E[\hat{\Psi}^h]$ and $E[\tilde{\Psi}_h]$ to Ψ_h . If $\hat{\Psi}$ is strongly biased, its powered value diverges from Ψ^h as h increases, while the bias in $\tilde{\Psi}_h$ will most often be independent of h . In that case, the direct forecast, albeit less efficient, yields lower mean squared forecast error than the iterated forecast (Findley [1983]). In accordance with the result provided herein and owing to the fact that multivariate models are prone to misspecification, we adopt the direct forecasting method for the baseline AR and VAR models. The literature being more silent about the choice of iterated versus direct forecast regarding non-parametric models, we adopt direct forecasting for all models to ensure comparability across models.

Our analysis aims at assessing marginal predictive content of financial variables beyond the information contained by current and past economic conditions. To control for the persistence of macroeconomic shocks and their ensuing intrinsic predictability, we therefore include lagged values of Industrial Production. The number of lags is common to all models and forecasting horizons, and is chosen so as to minimize the information criterion of a VAR model. For the sake of parsimony, we only include the contemporaneous value of financial variables variables.

The generic problem for the h -period ahead forecasting model $g(\cdot)$ can be stated as follow:

$$y_{t+h}^h = g(X_t, y_t, \dots, y_{t-p}; \theta; \mathcal{H}) + \varepsilon_{t+h}$$

where y_t and y_{t+h}^h denotes Industrial Production at time t and its h -period ahead forecast respectively. X_t denotes a vector of financial variables. θ is a vector of parameters to be estimated, \mathcal{H} is a vector of hyperparameters to be calibrated for Machine Learning algorithms and p is the number of lags of the endogenous variable. ε_{t+h} is a stochastic i.i.d error process with mean zero and constant variance. For each Machine Learning algorithms, for each horizon and each period, the hyperparameters are chosen by cross-validation over a minimal number of observations deemed sufficient to train the model.

Once $\hat{\theta}$ is estimated, we can compute:

$$\hat{y}_{t+h}^h = g(X_t, y_t, \dots, y_{t-p}; \hat{\theta}; \mathcal{H})$$

Because we work in pseudo out-of-sample, we observe the true y_{t+h}^h and the model forecasting performance is evaluated based on the forecast error $y_{t+h}^h - \hat{y}_{t+h}^h$ for a given loss function.

The benchmark model

The benchmark model is an Autoregressive (AR) model. Autoregressive models, popularized by [Box and Jenkins \[1970\]](#), are natural benchmarks because they are hard to beat with multivariate models ([Marcellino et al. \[2003\]](#)). The main assumption of that kind of models is that persistence is the main source of fluctuations in a variable. The h -period ahead forecasting model is the following:

$$y_{t+h}^h = \alpha + \sum_{i=0}^p \beta_i y_{t-i} + \varepsilon_{t+h}$$

Asset prices may be informative for future prospects to the extent that investors are fully confident about the economic forecasts underpinning their investment decision. Asset prices may thereby reflect meaningful expectations about the short run, which warrants the focus on one to six months ahead forecasting.

The Bayesian VAR model

The most standard multivariate forecasting model is the Bayesian Vector Autoregressive model (BVAR). Unlike unrestricted VAR models, which tend to suffer from the “curse of dimensionality” and to attribute too much of the variance in time series to their deterministic components, BVAR are more flexible. [Litterman \[1985\]](#) and [Doan et al. \[1984\]](#) proposed Bayesian estimation to improve the estimation of large-scale VAR models. Bayesian inference treats the VAR parameters as random variables after having observed a sample of data. It allows to update probability distributions about the unobserved parameters conditional on the observed data and to incorporate prior information about the model parameters that summarize pre-sample information. Priors about the model coefficients have the same effect than penalized regressions in the frequentist case, they reduce parameter uncertainty and

improve forecast accuracy, at the cost of relatively small biases in the estimates of the parameters. In the context of BVAR, priors are not motivated by economic theory but are based on stylised representations of the data generating process of typical economic time series.

The advantage of using direct forecasting in a BVAR context is that in that case the h -step ahead forecast is still a linear function of the coefficients. Hence the direct approach provides closed form solutions for the multi-step forecasts, while the iterated approach are nonlinear functions of the estimated coefficients and require computationally intensive simulation techniques.

We estimate the following model:

$$y_t = c + A_1 y_{t-1} + \dots + A_p y_{t-p} + u_t, \quad \text{where } u_t \text{ i.i.d. } \sim \mathcal{N}(0, \Sigma)$$

Because u_t follows a multivariate Gaussian distribution, the distribution of y_t conditional on its past is Gaussian as well. Prior beliefs about the VAR coefficients are summarized by a probability density function and updated using Bayes' Law:

$$p(A, \Sigma | y_{1:t}) = \frac{p(A, \Sigma) p(y_{1:t} | A, \Sigma)}{p(y_{1:t})}, \quad \text{with } A = [A_1, \dots, A_p, c]'$$

The joint posterior distribution of the VAR(p) coefficients $p(A, \Sigma | y_{1:t})$ incorporates the information contained in the prior distribution $p(A, \Sigma)$ that summarizes the initial information about the model parameters and the sample information $p(y_{1:t} | A, \Sigma)$.

Because the innovations are i.i.d., the likelihood of the VAR conditional on the p first observations can be written as the product of the conditional distribution of each observation:

$$p(y_{1:T} | A, \Sigma, y_1, \dots, y_p) = \prod_{t=1}^T p(y_t | A, \Sigma, y_{t-p}, \dots, y_{t-1}).$$

Under the assumption of Gaussian errors:

$$p(y_{1:T} | A, \Sigma, y_1, \dots, y_p) = \prod_{t=1}^T \frac{1}{(2\pi)^{n/2}} |\Sigma|^{-1} \exp \left[-\frac{1}{2} (y_t - A' x_t)' \Sigma^{-1} (y_t - A' x_t) \right]$$

with $x_t' = [y_{t-1}', \dots, y_{t-p}']$.

Regarding the choice of priors, we follow [Koop et al. \[2010\]](#) and [Del Negro and Schorfheide \[2011\]](#) and use the Minnesota priors developed by [Doan et al. \[1984\]](#). [Marcellino et al. \[2006\]](#) indeed show that simple BVAR with Minnesota priors have good forecasting performances. In addition, these priors have a minimal computational cost because they can be cast in the form of a Normal-Inverse-Wishart prior. The Normal-Inverse-Wishart prior is the conjugate prior for the likelihood of a VAR with normally distributed disturbances, which mean that the posterior distribution belongs to the same family than the prior probability distribution. As a result, there is no need to use Markov Chain Monte Carlo simulation to draw from the

posterior distribution and compute the mean of the posterior distribution. This analytical tractability of the posterior distribution is very appealing given that our validation exercise requires to estimate a large number of models. The description of the Minnesota priors can be found in the [Appendix](#).

The Factor Augmented Autoregressive Distributed Lag models

[Hatzius et al. \[2010\]](#) suggest that condensing the information embedded in a large number of variables improves the forecasting power of financial indicators relative to individual series. To this end, we estimate a Factor Augmented Autoregressive Distributed Lag (FADL) model. We first compute financial static or dynamic factors that are then included in a linear model as such:

$$y_{t+h}^h = \alpha_h + \beta_h(L)\hat{f}_t + \gamma_h(L)y_t + \varepsilon_{t+h}$$

where $\beta_h(L)$ and $\gamma_h(L)$ are finite order lag polynomials and \hat{f}_t are the static or dynamic factors estimated beforehand.

Second-difference transformations on some of the variables may give rise to overlapping observations and therefore yield a moving average error term that invalidates ordinary least squares estimation ([Hansen and Hodrick \[1980\]](#)). We therefore use the Newey-West standard errors to correct for the autocorrelation and heteroskedasticity of the residuals. The computation of static factors is done by Principal Component Analysis (PCA). The number of static factors is selected using the information criterion of [Bai and Ng \[2002\]](#), which suggests 4 factors on average across all horizons and periods. We keep the same number in the dynamic and the static case to ensure consistency¹³. The dynamic factor model is estimated as a multivariate auto-regressive state-space model, where the factors f_t are the state variables. The model consists in a measurement and a transition equation:

$$\begin{cases} y_t = Zf_t + v_t, & \text{where } v_t \sim \text{MVN}(0, R) \\ f_t = Af_{t-1} + w_t, & \text{where } w_t \sim \text{MVN}(0, Q) \end{cases}$$

The model is not yet identified and requires additional restrictions on the parameters. We follow [Harvey \[1989\]](#) and use the following parameter restrictions: 1) The autoregressive matrix A is the identity matrix (no granger-causality between factors); 2) In the first $m - 1$ rows of Z , $z_{i,j} = 0$ if $j > i$ (where m is the number of hidden factors); 3) The covariance matrix Q of the residuals in the transition equation is the identity matrix. Under these restrictions, the parameters are estimated via the Expectation-Maximization algorithm ([Dempster et al. \[1977\]](#)) which provides an iterative procedure for identifying the maximum likelihood estimates by using the Kalman Filter ([Kalman \[1960\]](#)) to compute the conditional expected value of the latent state variables and obtain the parameters estimates.

¹³According to [Bai and Ng \[2007\]](#), it is possible, however, that the number of dynamic factors is lower than the number of static factors.

4.4.2 The Bayesian Structural Time series model

Bayesian Structural Time Series (BSTS) is a state-of-the-art technique at the crossroads of structural econometrics and Machine Learning. The first layer is a structural time series model (see [Harvey \[1989\]](#)) with a regression term. The observation equation relates the observed data y_t to a latent trend μ_t , a seasonal component τ_t and a set of K regressors x_t :

$$y_t = \mu_t + \tau_t + \beta^T x_t + \varepsilon_t \quad \text{with } \varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2)$$

In our case, the local level term captures medium-term fluctuations in the first-difference of the logarithm of Industrial Production. The transition equation describes the law of motion of the latent variables:

$$\begin{aligned} \mu_{t+1} &= \mu_t + \eta_t \quad \text{with } \eta_t \sim \mathcal{N}(0, \sigma_\eta^2) \\ \tau_t &= - \sum_{s=1}^{11} \tau_{t-s} + \zeta_t \quad \text{with } \zeta_t \sim \mathcal{N}(0, \sigma_\zeta^2) \end{aligned}$$

The Kalman filter and smoother are used to compute the distribution $p(\mu_{t+1}|y_{1:t})$ and $p(\mu_t|y_{1:T})$ respectively, for each $t < T$. Because all components of the model are Gaussian, $p(\mu_{t+1}|y_{1:t})$ and $p(\mu_t|y_{1:T})$ follow multivariate normal distributions and are therefore fully pinned down by their means and variances, which are updated at each time step.

The coefficient of the regression term is estimated from a Bayesian perspective with the “spike-and-slab” priors of [George and McCulloch \[1997\]](#) and [Madigan and Raftery \[1994\]](#) which help to build a parsimonious model from a large set of potentially correlated regressors. The “spike” priors perform feature selection within the set of regressors. Then, conditional on a variable being in the regression, the “slab” priors describe the values that the coefficient can take on. Let $\gamma = (\gamma_1, \dots, \gamma_K)$ denote a vector of 1s if the corresponding variable is selected and 0s otherwise. According to Bayes’ law, the spike and slab priors can be factorized as follows:

$$p(\beta, \gamma, \sigma_\varepsilon) = p(\beta|\gamma, \sigma_\varepsilon)p(\sigma_\varepsilon|\gamma)p(\gamma)$$

The spike prior is assumed to follow a Bernoulli distribution:

$$\gamma \sim \prod_{k=1}^K \pi^{\gamma_k} (1 - \pi_k)^{1-\gamma_k}$$

where the parameter π can be set according to the expected model size¹⁴. The slab priors are assumed to follow a normal distribution. Draws from these two prior distributions are combined with the likelihood to obtain posterior draws of both the probability of inclusion and the coefficients. Posterior inference for the model parameters θ is performed via Markov Chain Monte Carlo (MCMC) simulation to generate draws of the model parameters given the observed data. The Gibbs sampler is used to simulate a sequence $(\theta, \alpha)^{(1)}, (\theta, \alpha)^{(2)}, \dots$ from a Markov chain whose stationary distribution is $p(\theta, \alpha|y_{1:n})$. The sampler alternates between a data-augmentation step that simulates from $p(\alpha|y_{1:n}, \theta)$ through the posterior simulation al-

¹⁴For instance $\pi = p/K$ if the expected number of predictors is p .

gorithm (Durbin and Koopman [2002]) and a parameter-simulation step that simulates from $p(\theta|y_{1:n}, \alpha)$.

4.4.3 Regularization techniques

Regularization techniques are linear methods that allow to deal with the “bouncing beta” problem of estimating a linear model with a large number of correlated regressors, that is the tendency of these models to be unstable and to perform poorly out-of-sample. Regularization techniques can improve upon least squares estimation by reducing the complexity of the model, which results in lower variance of the estimates. Regularization techniques deliberately introduce bias in the least-square estimation by adding a small penalty. This penalty biases all coefficients towards zero but reduces the variance of the model when new information arises.

The Ridge and the Lasso regression minimizes the following quantities over $\beta = (\beta_1, \dots, \beta_p)$:

$$\text{RSS} + \lambda \sum_{j=1}^p \beta_j^2 \quad \text{and} \quad \text{RSS} + \lambda \sum_{j=1}^p |\beta_j|, \quad \text{respectively}$$

where

$$\text{RSS} = \sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ij} \right)^2$$

The shrinkage penalties have the effect of shrinking the estimates of β_j towards zero. $\lambda \geq 0$ is a tuning parameter that serves to control the degree of departure from the least-square estimator. Higher λ has the effect of minimizing variance and increasing bias. The main difference between the Ridge and the Lasso regression is that the Ridge penalty tend to shrink all coefficients proportionately and to equalize the coefficients on correlated data, while the Lasso penalty focuses on a small subset of these variables.

The elastic net regression seeks a compromise between parsimony and the inclusion of correlated predictors. The elastic net minimizes over β :

$$\text{RSS} + \lambda \left[\alpha \sum_{j=1}^p \beta_j^2 + (1 - \alpha) \sum_{j=1}^p |\beta_j| \right]$$

where α is the weight of the Ridge penalty relative to the Lasso penalty.

4.4.4 Decision Tree algorithms

Decision Tree is a class of Machine Learning algorithms that are able to deal with a large number of predictors and to perform estimation and variable selection simultaneously. They are ideally suited to model non-linear and complex relationships. Tree-based methods involve segmenting the predictor space X_1, X_2, \dots, X_p into J distinct and non-overlapping regions R_1, R_2, \dots, R_J (see Figure 4.3). For every observation that falls into the region R_j , the

prediction is the mean of the response values for the training observations in R_j . A Regression Tree assumes a model of the form:

$$f(X) = \sum_{j=1}^J \beta_j \cdot \mathbb{1}_{X \in R_j}$$

Mathematically, the optimization problem consists in finding boxes R_1, \dots, R_J in order to minimize the Residual Sum of Squares given by:

$$\sum_{j=1}^J \sum_{i \in R_j} (y_i - \hat{y}_{R_j})^2$$

where \hat{y}_{R_j} is the mean response for the training observations within the j -th box and y_i is the corresponding target value. Starting from the top of the tree, the partition is done by recursive binary split of the predictors. At each branch of the tree, the predictor X_j and the cutpoint s are chosen such that the predictions into the regions $\{X|X_j < s\}$ and $\{X|X_j \geq s\}$ yield the lowest RSS. To mitigate the risk of overfitting, the tree is usually pruned by penalizing the number of terminal nodes. Smaller tree with fewer splits help to shrink the parameters variance at the cost of a little bias.

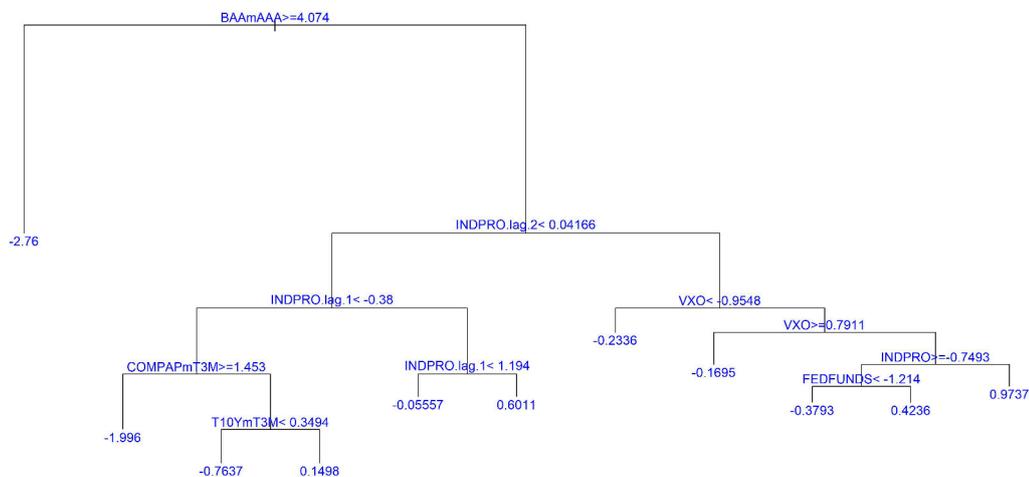


Figure 4.3: A simple Regression Tree

Individual Regression Trees are easy to interpret but prone to overfitting. A natural solution to improve the out-of-sample performances of Regression Trees is to combine a large number of trees with Random Forests, Bagged Trees or Boosted Trees. Bagging is a general-purpose procedure to increase the prediction accuracy of a statistical learning method by averaging multiple models to reduce the variance. In the context of Regression Trees, bagging consists in growing a large number of trees over bootstrapped samples¹⁵ from the same

¹⁵The idea behind bootstrap is to take repeated samples from the same set of observations when only one

training set. The final prediction averages the predictions over these sets. Because bagging reduces the variance¹⁶, it can be applied to trees that are not pruned.

The idea behind Random Forests is similar to that of bagging. A large number of unpruned decision trees is grown on bootstrapped training samples. However, for each tree, instead of considering all predictors, each time a split is considered, a random sample of m predictors is chosen from the set of p predictors (typically $m = \sqrt{p}$). The rationale behind excluding a large part of the available predictors is that this procedure yields very different trees, while bagged trees tend to be very correlated (for instance because the splits at the top of the tree always involve the strongest predictors). On average, each predictor will be excluded for $(p - m)/p$ splits, regardless of its predicting power. As a result, Random Forests improve significantly prediction accuracy by reducing the variance relative to bagged trees.

A final method to improve the performances of Regression Trees is based on Boosting. Boosting is a general-purpose procedure that combines models that do not perform particularly well individually into one with improved properties. Boosted Trees are grown sequentially using information from previously grown trees instead of growing trees independently as in Bagging or Random Forests. Boosting iteratively fits Decisions Trees with the residuals of the previous ensemble. The new Decision Tree is then added to the fitted function, thereby improving the model in areas where it does not perform well. The algorithm works as follow:

1. Set $\hat{f}(x) = 0, \forall x \in X$ and $r_i = y_i$ for all i in the training set
2. For $j = 1, \dots, n$ repeat:
 - (a) Fit a tree \hat{f}_j with d splits to the training data (X, r)
 - (b) Update \hat{f} by adding a shrunken version of the new tree:

$$\hat{f}(x) \leftarrow \hat{f}(x) + \lambda \hat{f}_j(x), \quad \text{where } \lambda \text{ is the learning rate}$$

- (c) Update the residuals:

$$r_i \leftarrow r_i - \lambda \hat{f}_j(x_i)$$

The final model is $\hat{f}(x) = \sum_{j=1}^n \lambda \hat{f}_j(x)$.

The hyperparameters for Boosted Trees, Random Forests and Bagged Trees are calibrated so as to minimize the out-of-bag error¹⁷. This is carried out for all forecasting horizons and for both forecasting periods. Moreover, the number of decision trees is chosen sufficiently large that the error has settled down¹⁸.

training set is available.

¹⁶Given a set of n independent observations X_1, \dots, X_n , each with variance σ^2 , the variance of the mean of the observations is σ^2/n .

¹⁷For a given observation, the out-of-bag error is the prediction error of trees that were built on samples excluding this particular observation

¹⁸Increasing the number of trees does not cause the models to overfit (Hastie et al. [2009]).

4.4.5 Artificial Neural Networks

Artificial Neural Networks belong to a specific subfield of Machine Learning called Deep Learning, whereby multiple layers learn representations of the data with different levels of abstraction. They have been found to be universal approximations of any continuous function (Hornik et al. [1989]). While they have been extensively used in image and speech recognition or language processing, their use in macroeconomic forecasting has been relatively limited so far (see for instance Gonzalez et al. [2000], Cook and Hall [2017] and Bredahl Kock and Teräsvirta [2016]).

A Neural Network is made of an input layer¹⁹, an output layer and one or more hidden layers. The hidden layers filter progressively the data in order to make them more meaningful for the problem at stake. Figure 4.4 illustrates a simple model with two hidden layers of 3 and 2 neurons respectively and one output layer.

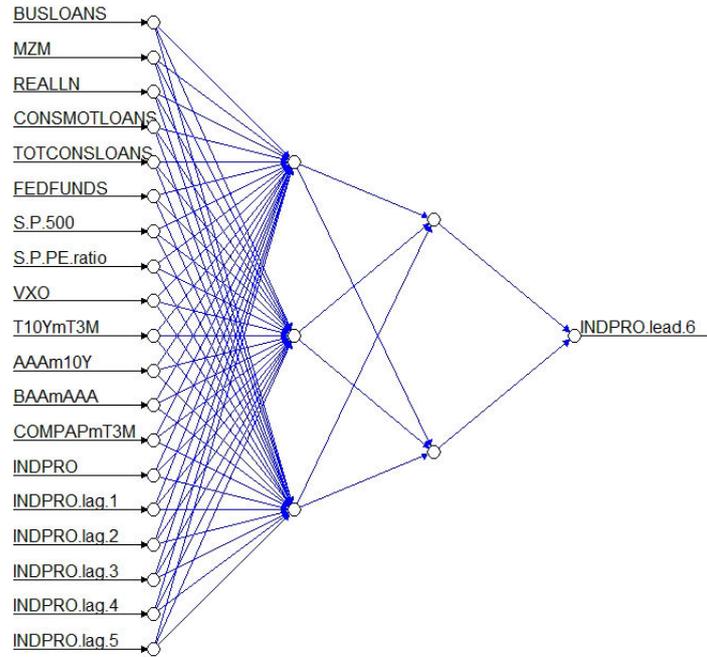


Figure 4.4: A simple Neural Network

We consider a general Neural Network N_θ , where $\theta = (w_1, \dots, w_N, b_1, \dots, b_N)$ denotes all the parameters of the network (weights and biases). Let $x_j^{(i)}$ represent the value of the j^{th} predictor, or input, for observation i . The training dataset is composed of pairs $\{(x^{(i)}, y^{(i)}) | 1 \leq i \leq n\}$, where $y^{(i)}$ is the predicted variable and $x^{(i)} = (x_1^{(i)}, \dots, x_n^{(i)})^T$. Learning consists in finding θ that minimizes the overall loss function:

$$E : \theta \rightarrow \frac{1}{n} \sum_{i=1}^n \mathcal{L}(N_\theta(x^{(i)}, y^{(i)})),$$

¹⁹A layer is a set of nodes, each node taking as input a weighted combination of the outputs of the nodes in previous layers and applying a non-linear transformation to it.

where \mathcal{L} is a loss function (typically squared errors for regression). Owing to non-linearities, the weights have to be optimized simultaneously. There is no analytical solution to this optimization problem and the local minimum has to be found algorithmically. The training algorithm minimizes E iteratively with an optimization procedure called the Gradient Descent algorithm. Each iteration t of a Gradient Descent routine updates current parameters θ_t such that:

$$\theta_{t+1} = \theta_t - A \nabla E|_{\theta_t}$$

where A is a projection matrix that determines the learning rate of the movement in the direction implied by $\nabla E|_{\theta_t}$, the gradient of E evaluated at θ_t :

$$\nabla E|_{\theta_t} = \left(\frac{\partial E}{\partial w_1}, \frac{\partial E}{\partial b_1}, \dots, \frac{\partial E}{\partial w_N}, \frac{\partial E}{\partial b_N} \right)$$

The gradient is a vector that points to the direction of the steepest increase of the function. If the partial derivative is negative (positive), the weight is increased (decreased), until a local minimum is reached. Therefore, moving the weights a little bit in the opposite direction of the gradient minimizes the loss function E . For the output of neuron j in layer l is given by:

$$h_j^l = \sigma \left(\sum_i w_{ij}^l h_i^{l-1} + b_j^l \right)$$

The weight $w_{ij}^l(t)$ at iteration t is given by:

$$w_{ij}^l(t+1) = w_{ij}^l(t) - \alpha \frac{\partial E}{\partial w_{ij}^l(t)}$$

where α is a scalar learning rate.

The gradient at the iteration t can be computed for $i = 1, \dots, N$:

$$\frac{\partial E}{\partial w_{ij}^l(t)} \approx \frac{E|_{\theta_t + h \cdot e_{ij}^l} - E|_{\theta_t}}{h}$$

where e_{ij}^l is one-hot vector and h is very small. In practice, the computation of $E|_{\theta_t + h \cdot e_{ij}^l}$ and $E|_{\theta_t}$ is intractable. A method called Backpropagation (Rumelhart et al. [1986]) makes it possible to compute the gradient of the error with respect to any weights via a single forward and backward pass through the network. The gradient is computed via the Chain Rule by taking the loss term found at the end of the forward pass and “propagating” the error backwards from the output layers to the input layers. Starting from random weights and biases, the training of Artificial Neural Networks consists in iterating the following steps until the number of epochs is reached. First, the prediction error is computed from the network output computed via forward propagation. Second, the error generated by the current weights and biases is returned via backpropagation and is used to update the parameters.

We illustrate the Backpropagation algorithm with a simple Neural Network with two

layers, one input x_1 and one output a_2 with the following structure:

$$z_1 : x_1 \rightarrow x_1.w_1 + b_1 \Rightarrow a_1 : z_1 \rightarrow \frac{1}{1 + e^{-z_1}} \Rightarrow z_2 : a_1 \rightarrow a_1.w_2 + b_2 \Rightarrow a_2 : z_2 \rightarrow \frac{1}{1 + e^{-z_2}}$$

For the mean-squared error loss, the error with respect to the target variable y is given by:

$$E = \frac{1}{2}(y - a_2)^2$$

Updating w_2 :

$$w_2 \rightarrow w_2 - \alpha \frac{\partial E}{\partial w_2}$$

with

$$\frac{\partial E}{\partial w_2} = \frac{\partial E}{\partial a_2} \cdot \frac{\partial a_2}{\partial z_2} \cdot \frac{\partial z_2}{\partial w_2}$$

with

$$\frac{\partial E}{\partial a_2} = -(y - a_2) ; \quad \frac{\partial a_2}{\partial z_2} = \frac{e^{-z_2}}{(1 + e^{-z_2})^2} = a_2(1 - a_2) ; \quad \frac{\partial z_2}{\partial w_2} = a_1$$

Therefore:

$$\frac{\partial E}{\partial w_2} = -(y - a_2) \cdot a_2(1 - a_2) \cdot a_1$$

Updating b_2 :

$$b_2 \rightarrow b_2 - \alpha \frac{\partial E}{\partial b_2}$$

$$\frac{\partial E}{\partial b_2} = \frac{\partial E}{\partial a_2} \cdot \frac{\partial a_2}{\partial z_2} \cdot \frac{\partial z_2}{\partial b_2}$$

Likewise we can easily update, w_1 and b_1 :

$$\frac{\partial E}{\partial w_1} = \frac{\partial E}{\partial a_2} \cdot \frac{\partial a_2}{\partial z_2} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z_1}{\partial w_1}$$

$$\frac{\partial E}{\partial b_1} = \frac{\partial E}{\partial a_2} \cdot \frac{\partial a_2}{\partial z_2} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z_1}{\partial b_1}$$

One limitation of vanilla feed-forward Neural Networks when it comes to time series prediction is that they cannot account for the sequential nature of the data. Recurrent Neural Networks (RNN) instead use their internal memory to process sequences of inputs. However, RNN also suffer from a setback called the “vanishing gradient” when the relationships between the input data are several steps apart. Because traditional activation functions have gradients in the range $]-1, 1[$ or $[0, 1[$, the error received for the current weight in each iteration will shrink asymptotically to zero as it back-propagates toward earlier layers. This means that the neurons in the earlier layers learn very slowly and imprecisely as compared to the neurons in the later layers, and the network is not able to learn long-term dependencies.

The Long Short-Term Memory (LSTM) model, first introduced by [Hochreiter and Schmidhuber \[1997\]](#), enhances RNN by allowing to model long-term relationships, which is appealing in the case of time series forecasting. LSTM solves the vanishing gradient problem by adding the updates instead of multiplying them. Like RNN models, the LSTM consists in the iteration of several similar network, each transmitting to its successor the input X_t as well as its

own output from the previous time step H_t . Unlike RNN models, however, the LSTM also produces an altered memory C_t that will be transmitted to the next iteration along with H_t . The memory is updated given the optimal degree of pass-through of old memory via a sigmoid activation function that controls whether additional information should be propagated further.

4.5 Forecast Evaluation

A good forecasting model should be able to reflect accurately the regularities of the training set and generalize well to new data. Any algorithm learning process however involves a trade-off between bias and variance of the estimated parameters. The bias is an error that arises from misspecifying the model, which leads to under-fitting. The variance reflects the sensitivity to small fluctuations in the data that leads to over-fitting in the training dataset and out-of-sample under-fitting. A well-known problem is that it is not possible to minimize simultaneously these two sources of error. Unlike parametric models, which assume some finite set of parameters, the complexity of non-parametric models grows with the size of the data used for estimation. These models are therefore more prone to over-fitting, as including too many degrees of freedom mechanically inflate the model's fit.

Cross-validation, a technique to assess if a statistical analysis generalizes to an independent data set, is a potential safeguard against these problems (Stone [1974]). In its simplest form, known as the holdout method, cross-validation consists in separating the data set between a training and a test set. The model is fitted for the training data and the prediction error, also referred to as the generalization error, is computed for the test set only. Cross-validation gives an unbiased measure of the true out-of-sample Mean Squared Error (MSE). Additionally, it decreases dramatically the likelihood that our results occurred simply by chance when too many combinations of variables are tested (the so-called data snooping bias). A more efficient way of performing cross-validation, called K -fold cross-validation, consists in dividing the dataset into k subsets. At each iteration, $k - 1$ observations are used for training and the remaining observations serve for testing. The average error across all k test sets is computed. By averaging over a large number of measures, the estimate of the out-of-sample forecast error has a lower variance compared to an error estimate that would use only one training and test split (Blum et al. [1999]). However, standard cross-validation techniques require the data to be i.i.d., i.e. drawn independently from fixed distribution. In the context of time series data, stationarity ensures that the distribution of the data is fixed over time. The assumption of independence, however, no longer holds because of persistence, which makes the use of cross-validation problematic (Bergmeir and Benítez [2012]). One way to ensure that the training and test sets are independent is to leave enough distance between the two in order to get rid of serial correlation. Modified versions of cross-validation for time series analysis have been proposed, such as Walk-Forward validation (see Figure 4.5).

With Walk-Forward validation, the model is first fitted on a training set with a minimum

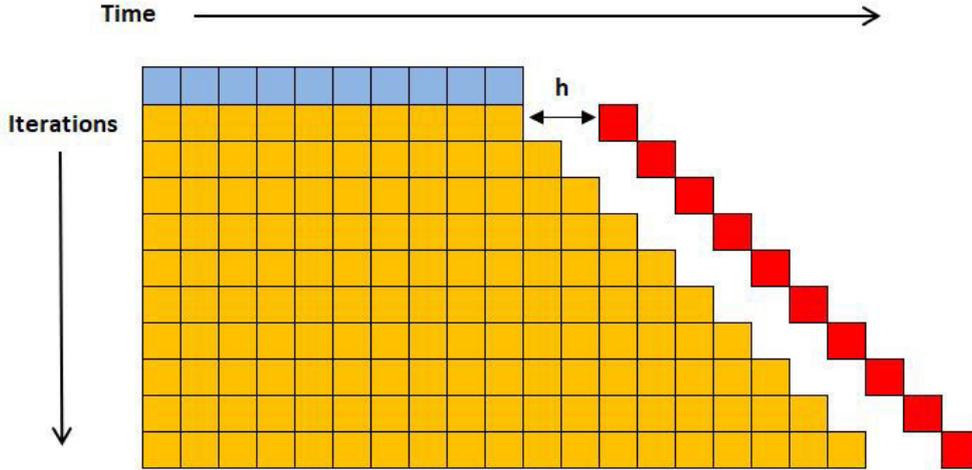


Figure 4.5: Walk-Forward Validation

set of observations located at the beginning of the sample. Then, the h -step ahead prediction starting from the end of the training set is evaluated against the known value. The training time window is then expanded forward with the following observation and the training and test process is repeated recursively until the length of the training set is equal to that of the full dataset minus the forecasting horizon. Walk-forward validation yields a more robust estimation of the out-of-sample forecasting error, at the computational cost however of fitting a large number of models. A major advantage of Walk-forward Validation is that it is realistic from the perspective of a real-time forecaster that updates his model to include as much information as possible. Importantly, the hyperparameters of the Machine Learning algorithms are optimized for each horizon by cross validation on data at the beginning of the sample that is not used for testing afterwards.

There are several ways to compare the forecasting performances of different models. Forecast encompassing (Chong and Hendry [1986]; Timmermann [2006]), for instance tests whether other models contain information about the forecast errors of a specific model, in which case these models should be included in the formation of a composite forecast. An alternative approach, that we adopt here, is to compare the forecast errors of competing models via a loss function. The task is to find the function $\hat{f}(X)$ that minimizes the expectation of some loss function $L(y, f)$:

$$\hat{f}(X) = \arg \min_{f(X)} E[L(y, f(X))]$$

We choose to rank the competing models according to the Root Mean-squared Error (RMSE). As shown by Marcellino [2000], a model that does not outperform other models in terms of RMSE does not forecast encompass them either. For a given forecast made by model M , the RMSE at horizon h over the sample $t = 1, \dots, T$ is:

$$RMSE_h(M) = \sqrt{\frac{1}{T} \sum_{t \in [1, T]} (\hat{y}_{t+h}(M) - y_{t+h})^2}$$

where $\hat{y}_{t+h}(M)$ is the predicted value for y_{t+h} by model M .

However, the fact that a model’s RMSE is smaller than that of another model in a particular sample realization does not necessarily mean that this is true in population. To assess if better “in sample” performances are merely due to luck or truly indicative of a difference “in population”, we use the diagnostic test of [Diebold and Mariano \[2002\]](#), which is an asymptotic z-test of the hypothesis that the loss differential between two competing models is zero, with heteroskedasticity and autocorrelation robust standard errors. Under the condition that the difference between the loss functions d is covariance stationary, the Diebold-Mariano test statistic is:

$$\frac{\bar{d}}{\hat{\sigma}_{\bar{d}}} \sim \mathcal{N}(0, 1)$$

where $\bar{d} = \frac{1}{T} \sum_{t=1}^T d_t$ is the sample mean loss differential and $\hat{\sigma}_{\bar{d}}$ is a consistent estimate of the standard deviation of d .

4.6 Results

4.6.1 Forecasting performances

We first investigate through the lens of the specific strengths and weaknesses of a battery of model the well-known instability of financial variables predictive power. We first report the out-of-sample RMSE relative to the Autoregressive model ([Table 4.4](#)). A lower than one Relative RMSE means that the model performs better “in sample” than the simple persistence model. We also indicate the statistical significance of the Diebold-Mariano test, whereby the null-hypothesis is that the forecast error of the model is equal to that of the Autoregressive model.

Several results stand out from this analysis. First, as often with macroeconomic forecasting, the naive autoregressive model is hard to beat, owing to the strong level of persistence of Industrial Production. The results also suggest that before the Great Moderation, financial variables contained useful information about future economic outcomes. Regarding the second period, however, results are more mixed and financial variables seem to have lost relevance over time. This is all the more surprising that the structural changes surrounding the Great Moderation theoretically should have improved price discovery and reduced the noise surrounding financial prices. Yet, a failure to beat the autoregressive model does not mean that multivariate models should systematically be discarded. In particular, multivariate models, unlike autoregressive models, are helpful when it comes to understanding why financial variables could anticipate the Business Cycle.

Turning to the specific forecasting performances of each models, a few salient facts emerge. First, the BVAR model systematically underperform the autoregressive model. Albeit counterintuitive, this is in line with the results of [Canova \[2011\]](#) about inflation forecasts. One reason for that, also supported by the poor forecasting performances of the Bayesian Struc-

Table 4.4: Relative Root Mean Square Error

1963-1985						
	h=1	h=2	h=3	h=4	h=5	h=6
BSTS	1.54 ***	1.57 ***	1.53 ***	1.47 ***	1.6 ***	1.4 ***
FADL	0.77 ***	0.79	0.8	0.8	0.87	0.87
Bagged trees	0.92	0.86	0.87	0.87	0.87	1
Random forest	0.92	0.86	0.87	0.87	0.87	0.93
Boosted trees	1.08 **	1 *	0.93	1	0.93	1
Elastic net	0.85 *	0.86	0.87	0.87	0.93	1
Neural net	1.08	0.98	1.13 **	1.21 ***	1.05	1.08
BVAR	1.08 **	1 **	1.13 ***	1.2 ***	1.33 ***	1.33 ***
1986-2016						
	h=1	h=2	h=3	h=4	h=5	h=6
BSTS	1.4 ***	1.7 ***	1.7 ***	1.36 ***	1.5 ***	1.25 ***
FADL	1 ***	0.9 *	0.9 *	0.91	0.83	0.92
Bagged trees	1.2	1.2	1.2	1.18	1.08	1
Random forest	1.1	1.1	1.2	1.09	1.08	1
Boosted trees	1.2 **	1.2 **	1.2 *	1.18 **	1.08 **	1.17
Elastic net	1	1	1	1.09	1	1
Neural net	1.12 **	1.23 *	1.12	1.32 ***	1.48 ***	1.43 **
BVAR	1.2 ***	1.3 ***	1.3 ***	1.45 ***	1.17 **	1.25 ***

*p<0.01; **p<0.05; ***p<0.1

tural Time Series model, could be that Bayesian shrinkage is not suited to handle such a large number of variables at low-frequency.

Unlike Bayesian models, the models featuring data reduction and feature selection yield encouraging results. The forecasting performances of the FADL model²⁰, the Elastic Net model and Regression Tree models, suggest that a data-driven selection process is key to ensure parsimony with no further ad-hoc assumption on the relative importance of individual variables. Automatic data selection is appealing because, as we will see later, financial variables tend to be complementary over time.

Allowing for non-linear relationships between financial variables and economic activity appears to be less important for the extraction of the economic content of financial variables. In particular, the performance of the Artificial Neural Network is relatively underwhelming given the promise of such models. More precisely, as suggested by the performances of the Regression Tree models, the type of non-linearity matters. Abrupt non-linearities seem to be better suited than continuous non-linear transformations to approximate the underlying Data Generating Process. The poor performances of Artificial Neural Network should, however, be interpreted with caution. In particular, hyperparameters such as the batch size or the number of epochs²¹ are optimized only once at the beginning of the training sample and are

²⁰We only show the results of the best FADL model among static and dynamic factors.

²¹An epoch consists in one forward pass and one backward pass through the Neural Network of all the

then kept constant to ensure fairness and comparability with the other algorithms. Artificial Neural Networks tend to be very sensitive to the choice of these parameters and finding a good balance between in-sample goodness-of-fit and proper out-of-sample generalization can be computationally demanding. Therefore, it is also possible that our one-size-fits-all calibration method dampens the forecasting performances of the Artificial Neural Network model.

In addition to unconditional forecasting performance, we study whether forecast errors are state-dependent. For each model, we regress the square of the forecast errors on a dummy variable capturing Business Cycle turning points. To this end, we use the turning points indicator of the OECD²², that we transform such that 1's designates specifically peaks and troughs dates. Table 4.5 shows coefficient estimates for the turning point indicator, as well as their statistical significance. For most models, we find a positive and statistically significant relationship between one-month ahead forecast errors and turning points during the first period, suggesting that forecasting models tend to perform badly around turning points. At higher horizons and for the second period, however, we find no evidence of state-dependence in forecasting errors.

training sample. The batch size is the number of training observations in a forward/backward pass, as it is not possible to pass the entire dataset into the neural net at once.

²²Turning points are measured and identified on deviation-from-trend series.

Table 4.5: State-dependence of forecast errors

1963-1985							
	h=1	h=2	h=3	h=4	h=5	h=6	
AR	0.049 ***	-0.005	0	-0.01	-0.001	-0.008	
BSTS	0.057 ***	-0.004	-0.001	0	0.043	-0.007	
FADL	0.015 **	-0.005	-0.001	0.002	0.026 ***	0.01	
Bagged trees	0.025 ***	0.003	0.001	-0.003	0.026 ***	0.021	
Random forest	0.028 ***	0.004	0.002	-0.004	0.025 ***	0.011	
Boosted trees	0.026 ***	0.015	0.02 *	-0.012	0.014	-0.008	
Elastic net	0.021 ***	-0.002	-0.001	0	0.041 ***	0.02	
Neural net	-0.009	-0.016	-0.017	0.037 *	0.195 ***	0.072 *	
BVAR	0.046 ***	0.001	-0.007	-0.016	0.002	-0.008	
1986-2016							
	h=1	h=2	h=3	h=4	h=5	h=6	
AR	0.001	-0.004	0.009	0.014	0.022 *	0.014	
BSTS	-0.005	-0.017	0	0.005	0.007	0.006	
FADL	0	-0.004	-0.002	0	0.003	-0.001	
Bagged trees	-0.003	0.001	0.001	0.014	0.032 *	0.005	
Random forest	-0.003	-0.005	0.001	0.007	0.022	0.004	
Boosted trees	0.001	-0.001	-0.002	-0.007	0.005	0.011	
Elastic net	-0.003	-0.005	0	0.004	0.009	0.005	
Neural net	0.096	0.078 ***	50.059 ***	0.473 ***	0.017	0.003	
BVAR	0	0.006	0.012	0.044 *	0.025 *	0.013	

*p<0.01; **p<0.05; ***p<0.1

4.6.2 Importance analysis

In addition to the aggregate predictive power of financial variables, we explore the information content of financial variables across the two periods. Most supervised Machine Learning algorithms allow to measure the relative importance of each of the predictors. For each Machine Learning algorithm, as well as for the FADL model, we estimate for each horizon the model on the two sub-samples and provide in-sample measures of importance for each variable.

For the FADL model, importance is measured by the partial R^2 , which represents the variance explained by a factor once the impact of other factors and lags of Industrial Production is accounted for. Despite its poor forecasting results, the BSTS model is informative about importance variable because it allows to compute the probability that a variable is included with a non-zero weight by the spike prior over all MCMC sampling draws, as well as the average coefficient estimate. For the Elastic Net, variable importance is proxied by the coefficient estimates²³. The parameters of the Random Forest model and the Artificial Neural Network are not interpretable as such, but the importance of specific input variables can however be estimated via different methods²⁴. For the Random Forest we compute the

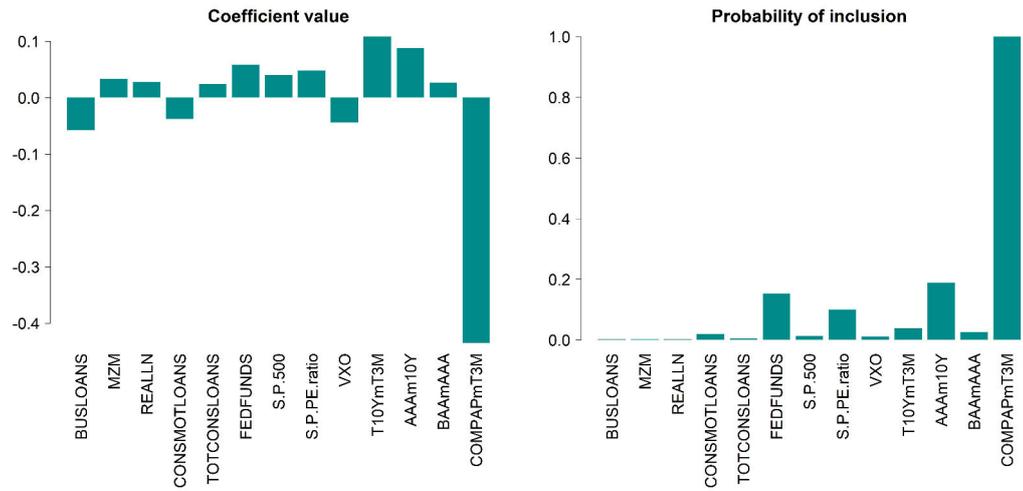
²³Considering the coefficient as a measure of importance in the context of a linear regression only makes sense because the variables have the same scale.

²⁴see Olden et al. [2004] for an overview of importance methods for Neural Networks.

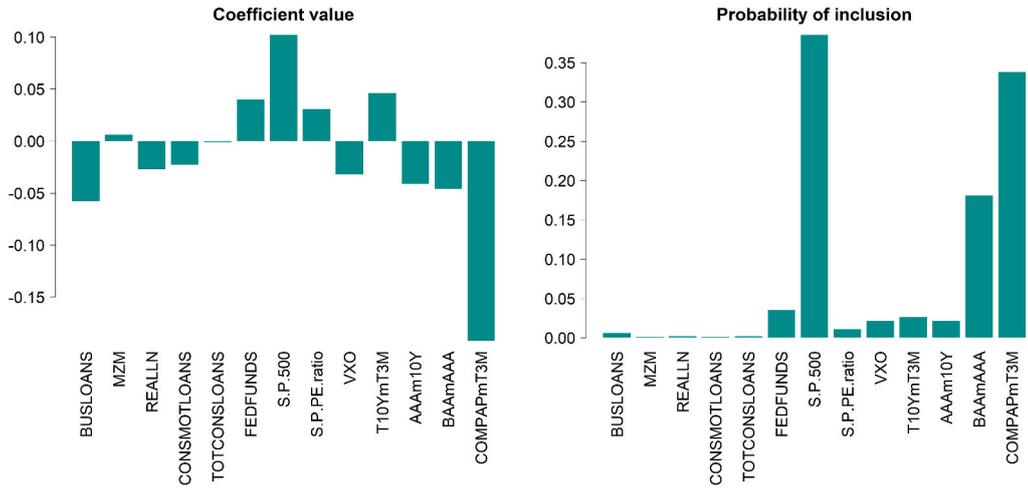
mean decrease of accuracy in predictions when a specific variable is excluded from the model. As regards the Artificial Neural Network, we follow the method of [Gevrey et al. \[2003\]](#), which is a simplified version of [Garson \[1991\]](#) that disentangle the hidden-output layer connection weights into components associated with the input-hidden layer connection weight of all input neurons. It is important to note that importance statistics are specific to each model and cannot be compared as such. Moreover, although it may be tempting to interpret importance statistics as a straightforward indication that some financial variables have better predictive power than others, they should be interpreted with caution, as they may reflect automatic variable selection among redundant but otherwise important variables. Because the results are relatively stable across forecasting horizons, in this section we only plot the mean of importance statistics across all horizons. Importance statistics for each horizon are provided in the [Appendix](#).

As shown by [Figure 4.6](#), the commercial paper spread has a high probability of being included with a large negative coefficient in the BSTS model. For the second period, corporate spreads (BAAmAAA) and stock prices (S.P.500) are also included frequently, with negative and positive coefficients respectively. Not surprisingly, the Elastic Net exhibits similar results ([Figure 4.7](#)), with commercial paper spreads being of paramount importance in both periods and stock prices only in the second period.

Figure 4.6: BSTS importance statistics

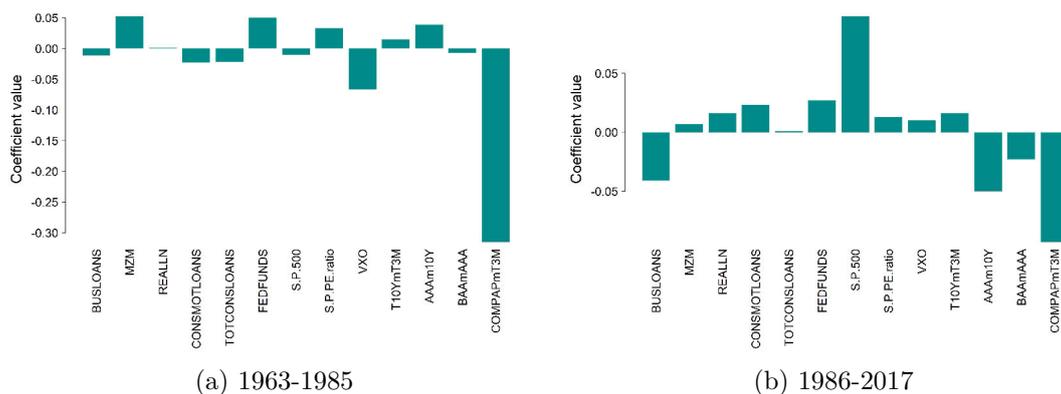


(a) 1963-1985



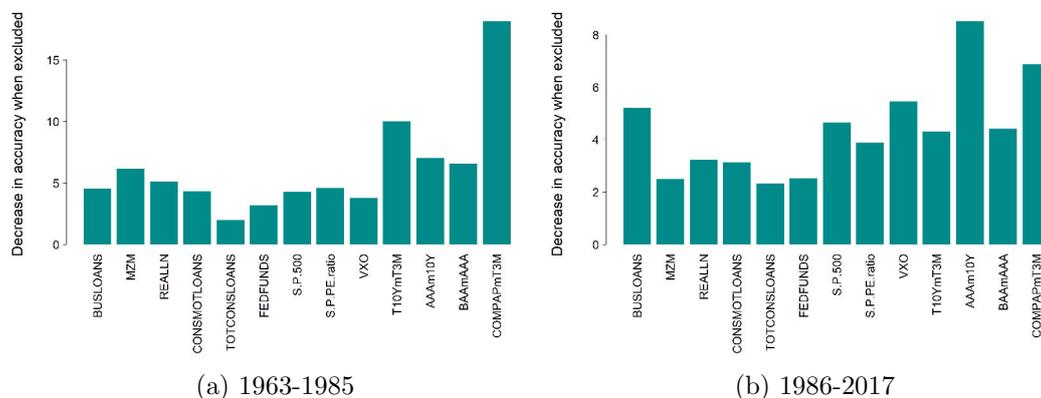
(b) 1986-2017

Figure 4.7: Elastic Net importance statistics



For the Random Forest algorithm, gains in accuracy are mostly related to the commercial paper spread and the term spread (Figure 4.8). While the former is more important than the latter in the first period, the opposite prevails in the second period. This is consistent with the results of Ng [2014], which stipulates that the term spread and credit spreads have independent and complementary explanatory power.

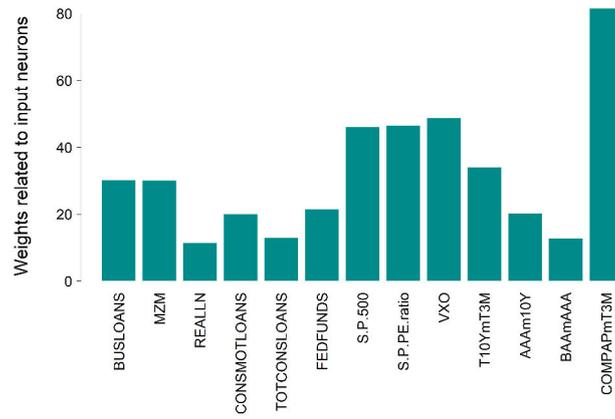
Figure 4.8: Random Forest importance statistics



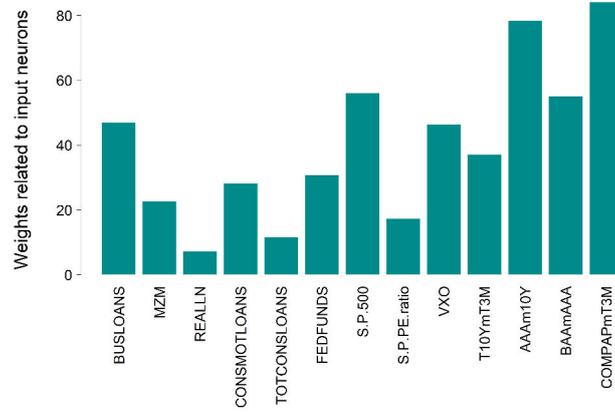
The Artificial Neural Network confirms the importance of the commercial paper spread, the term spread, stock prices and implied volatility (VXO) (Figure 4.9). The relative importance of volatility, especially in the first period, suggests that the information content of volatility for predicting output is likely to be non-linear.

Finally, for the FADL model, the second factor has strong marginal power (Figure 4.10), although it loads very differently on the financial variables over the two periods (Figure 4.11).

Figure 4.9: Neural Network importance statistics

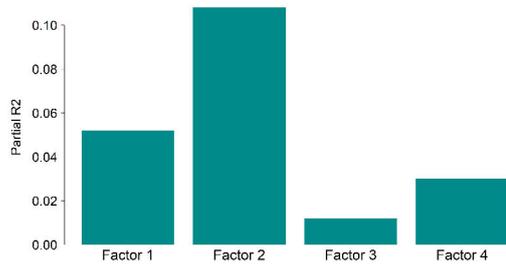


(a) 1963-1985

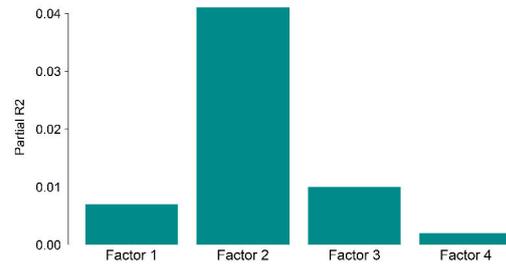


(b) 1986-2017

Figure 4.10: FADL importance statistics

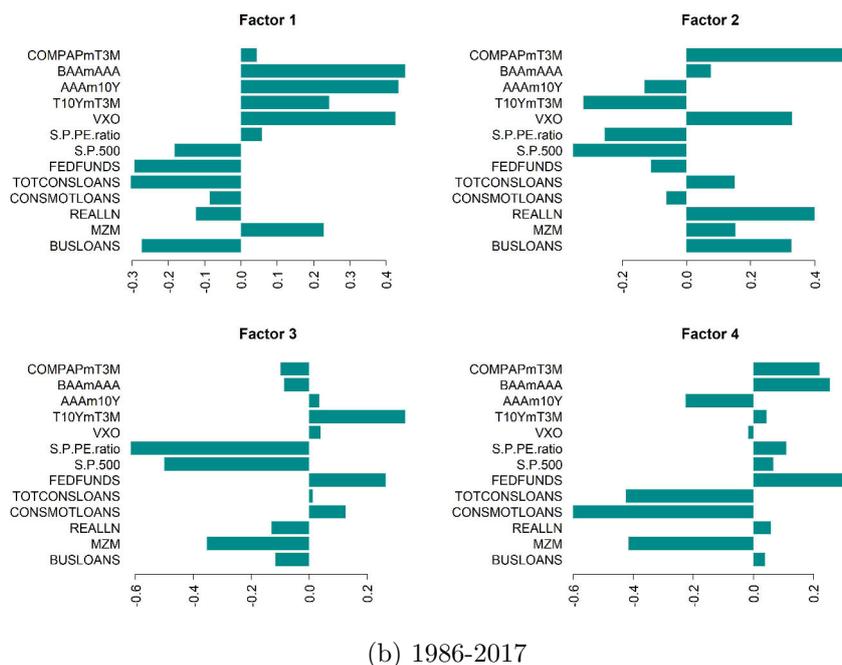
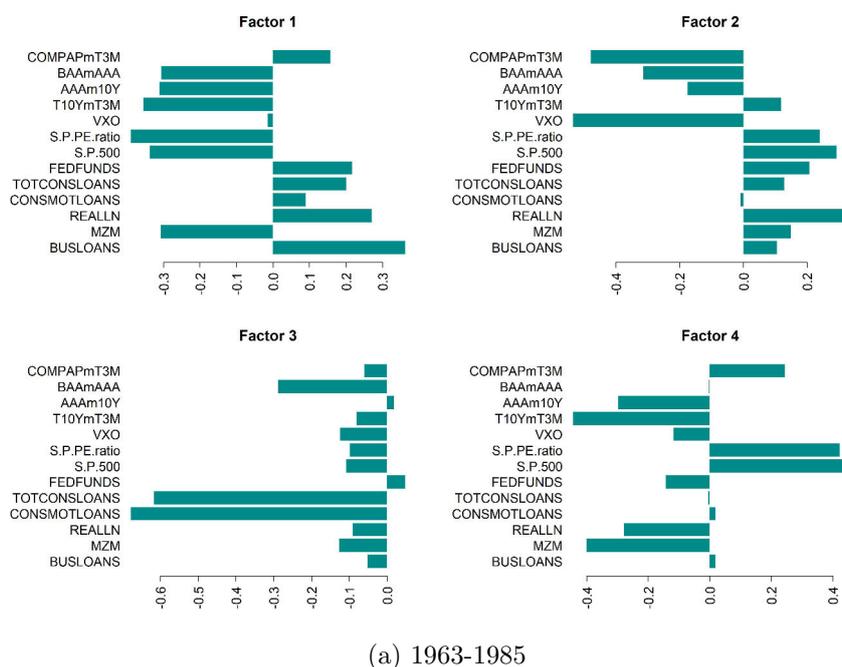


(a) 1963-1985



(b) 1986-2017

Figure 4.11: FADL Loadings



Over the first period, the second factor loads positively on equity variables (S.P.500 and S.P.PE.ratio), the Fed Funds rate (FEDFUNDS) and credit quantities (BUSLOANS, REALLN, CONSMOTLOANS), and negatively on corporate spreads (COMPAPmT3M, BAAmAAA) and implied volatility (VXO). The loadings suggest that the second factor represents the adverse effect of financial stress, proxied by corporate spread and implied volatility, on lending and the stock market. The prominence of such factor for economic activity is consistent with the findings of the literature on the real consequences of financial stress (Hubrich and Tetlow [2015]). Over the second period, the second factor loads positively on the commercial paper spread, implied volatility and credit quantities, and negatively on the term spread

(T10YmT3M) and equity variables. The interpretation of the factor is similar than in the first period, with the notable difference that credit quantities are now positively correlated with financial stress, owing for instance to the fact that financial stress spikes as a result of increasing leverage. The negative loading on the term spread bears upon its predictive power for recessions.

A few interesting facts stand out from these results. First, in line with previous forecasting exercises, price variables, such as corporate spreads, the term spread or equity prices, are more important for forecasting economic activity than quantity variables, such as money supply or loans volumes. This can be interpreted, albeit with caution, as an evidence that the predictive power of financial variables hinges more upon their forward-looking nature than their causal impact on economic activity. In the latter case, indeed, changes in financial prices should also manifest via changes in financial quantities, which in turn would correlate with future economic outcomes.

The considerable importance of short-term corporate spreads over the two periods is another striking result. This is reminiscent of the findings of [Bernanke \[1990\]](#), [Stock and Watson \[1989\]](#) and [Friedman and Kuttner \[1989\]](#)²⁵ in forecasting exercises, and of [Sims \[1972\]](#) which show via a VAR model that commercial paper interest rates explain a large proportion of the forecast variance of Industrial Production, thereby dwarfing the impact hitherto attributed to money. Moreover, in line with [Bernanke \[1990\]](#), we find that the predictive power of the commercial paper spread started to decrease in the 1980s. The importance of commercial paper spreads has two possible explanations. First, the spread embodies whatever information the market may have about the likelihood of a recession, via the perceived default risk of firms. A second channel, claimed by [Bernanke \[1990\]](#) to be more important than the previous one, is that commercial paper spreads are a proxy for the stance of monetary policy. Because of imperfect substitutability between Treasury bills and commercial paper, monetary policy affects the composition of assets available to investors and thereby the level of spreads. Finally, changes in commercial paper spreads modify the cost of external funding for firms and consequently their spending decisions.

We also find that the relative importance of financial variables is relatively stable across the two periods. This is somewhat surprising given the structural changes undergone by the financial sector in the 1980s. This finding may no longer hold, however, when adding financial variables directly linked to these structural changes, such as the leverage of non-bank intermediaries.

Overall, the results support the inclusion of several financial variables to benefit from their complementarity, having regard to the channels they bear upon, or their relevance across different phases of the Business Cycle. In this respect, the joint inclusion of corporate spreads, the term spread and stock prices, seems to be helpful to forecast economic activity.

²⁵The authors use the difference between the six-month commercial paper rate and the six-month Treasury bill rate.

4.7 Conclusion

The basic premise underlying this chapter was that a prerequisite of using financial variables to anticipate economic activity is to better understand the mechanisms underlying this relationship. To this end, we investigated whether considering non-parametric flexible models could alleviate the instability of financial variables' predictive power for economic activity. We computed the out-of-sample short-term forecasting performances of a battery of models including multiple financial variables and carried out in-depth analysis of the relative importance of each variable. Overall, our results confirmed that forecasting economic activity with financial variables is not a long calm river. In particular, the Great Moderation did not “purify” the signal returned by financial variables, as the predictive power of financial variables seems to have lessened over time. A noteworthy improvement over the two periods is that the forecast errors tend to be less correlated with turning points, which is desirable given the cost associated with poor forecasts when the economy faces a regime shift. We also found that the type of forecasting model matters. While a BVAR model would suggest that financial variables are of little help for predicting economic activity, allowing for more complicated interactions, along with data reduction or feature selection techniques, seems to improve signal extraction. The importance analysis moreover showed that the inclusion of several variables is helpful given their complementarity across periods and forecasting horizons. In this respect, automatic data selection techniques should be favored instead of choosing arbitrarily the variables that matter. Avenue for further research chiefly includes to improve our ability to disentangle the predictive power of financial variables between causal and forward-looking mechanisms.

Appendix C

Appendix - Chapter 4

C.1 The Minnesota priors

The Minnesota priors are based on the fact that an independent random-walk model for each variable in the system is a reasonable guess about their time series behavior. This materializes in a diagonal matrix structure for the prior mean of the coefficient matrices. This involves setting most parameters to zero. The Minnesota priors assume coefficients matrices to be independent and normally distributed such that:

$$E[A_i] = \text{diag}[\delta_1, \delta_2, \dots, \delta_n],$$

and

$$\text{Var}[A_i] = \frac{\lambda^2}{k^2} \begin{bmatrix} 1 & \theta\sigma_1^2/\sigma_2^2 & \dots & \theta\sigma_1^2/\sigma_n^2 \\ \theta\sigma_2^2/\sigma_1^2 & 1 & \dots & \theta\sigma_2^2/\sigma_n^2 \\ \vdots & \vdots & \ddots & \vdots \\ \theta\sigma_n^2/\sigma_1^2 & \theta\sigma_n^2/\sigma_2^2 & \dots & 1 \end{bmatrix}$$

The covariance matrix of the residuals is assumed to be a known diagonal matrix, such that:

$$\Sigma = \text{diag}[\sigma_1^2, \sigma_2^2, \dots, \sigma_n^2]$$

The Minnesota priors assume that the most recent lags are more important to provide reliable information than later lags. Therefore, the coefficient matrices should converge to 0, as the lags grow, i.e.:

$$E[|a_{ij}^1|] > E[|a_{ij}^2|] > \dots > E[|a_{ij}^p|] \rightarrow 0$$

The Minnesota priors drastically reduce the number of covariance parameters to be estimated. It imposes a single parameter λ/k to describe the belief of coefficient decay over lags. It uses another variable θ to describe the relative importance of own lags versus those of the others.

We calibrate the following Minnesota priors parameters by cross-validation for each fore-

casting horizon:

- The δ_i should lie between 0 and 1 and characterize the persistence of variables.
- λ is a positive parameter that controls the overall tightness of the prior distribution and the relative importance of the prior beliefs with respect to the observations. $\lambda = 0$ means that the posterior equals the prior and the data do not influence the estimates. $\lambda \rightarrow \infty$ means on the contrary that the posterior expectations coincide with the ordinary least squares (OLS) estimates.
- $\theta \in]0, 1[$ characterizes the relative importance of lags of other variables with respect to the own lags.
- $1/k^2$ is the rate at which the prior variance decreases with increasing lag length.
- The σ_i 's $\in]0, +\infty[$ characterize different scale and variability of the data, through elements σ_i^2/σ_j^2 in the covariance matrix of A_i .

C.2 Decomposition of the MSE

The MSE for h -period ahead forecasts can be decomposed as follows:

$$MSE(h) = \frac{1}{T} \sum_{t \in [1, T]} \left(\hat{y}_{t+h} - y_{t+h} \right)^2 \quad (C.1)$$

$$= (\mu_{\hat{y}_{t+h}} - \mu_{y_{t+h}})^2 + (\sigma_{\hat{y}_{t+h}} - \sigma_{y_{t+h}})^2 + 2(1 - \rho_{\hat{y}_{t+h}y_{t+h}})\sigma_{\hat{y}_{t+h}}\sigma_{y_{t+h}} \quad (C.2)$$

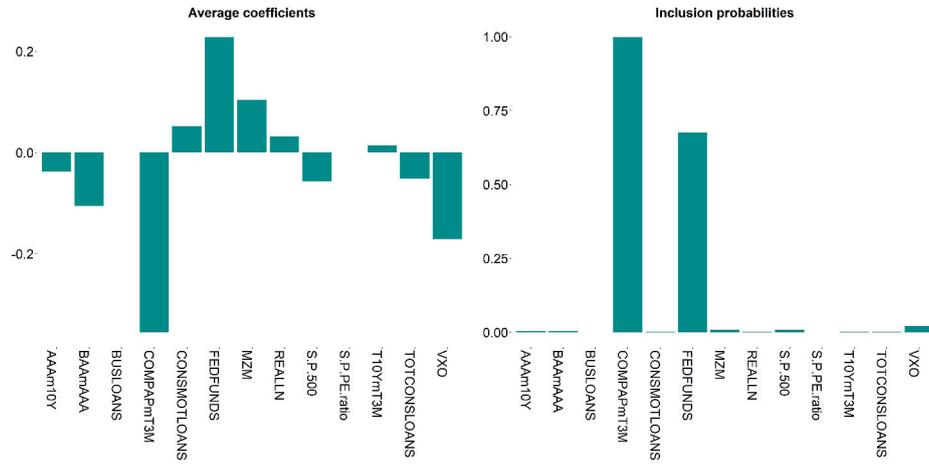
where $\mu_{\hat{y}_{t+h}}$ and $\mu_{y_{t+h}}$ are the means of the forecasted variable and of the true variable respectively, $\sigma_{\hat{y}_{t+h}}$ and $\sigma_{y_{t+h}}$ are the standard deviations of the forecasted variable and of the true variable, respectively and $\rho_{\hat{y}_{t+h}y_{t+h}}$ is the correlation between \hat{y}_{t+h} and y_{t+h} .

The bias, $(\mu_{\hat{y}_{t+h}} - \mu_{y_{t+h}})^2$, measures how far the mean of the forecast is from the mean of the actual series. The variance, $(\sigma_{\hat{y}_{t+h}} - \sigma_{y_{t+h}})^2$ measures how far the variance of the forecast is from the variance of the actual series. The covariance $2(1 - \rho_{\hat{y}_{t+h}y_{t+h}})\sigma_{\hat{y}_{t+h}}\sigma_{y_{t+h}}$ measures the remaining unsystematic forecasting errors. A good forecast should display low bias and variance.

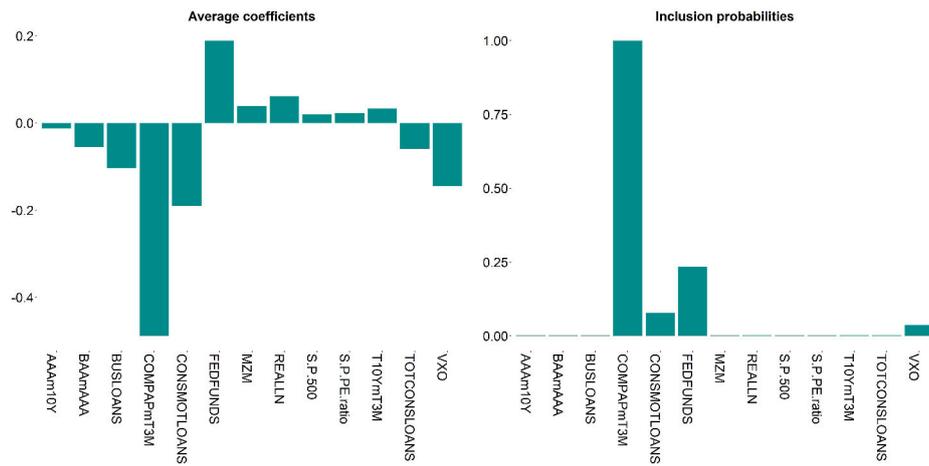
C.3 Importance analysis

C.3.1 Period 1

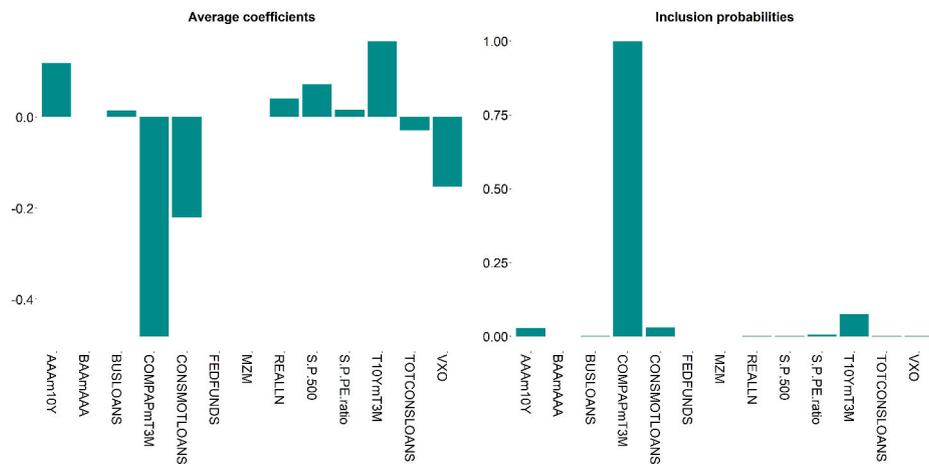
Figure C.1: BSTS importance statistics



(a) $h=1$

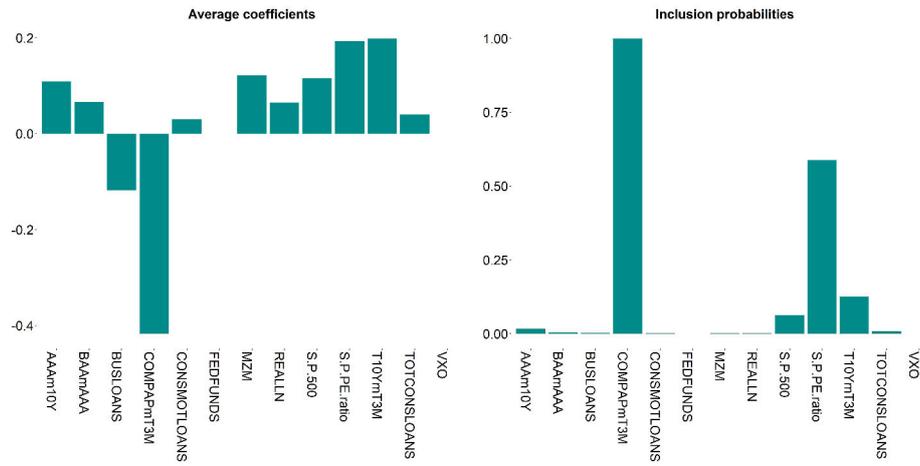


(b) $h=2$

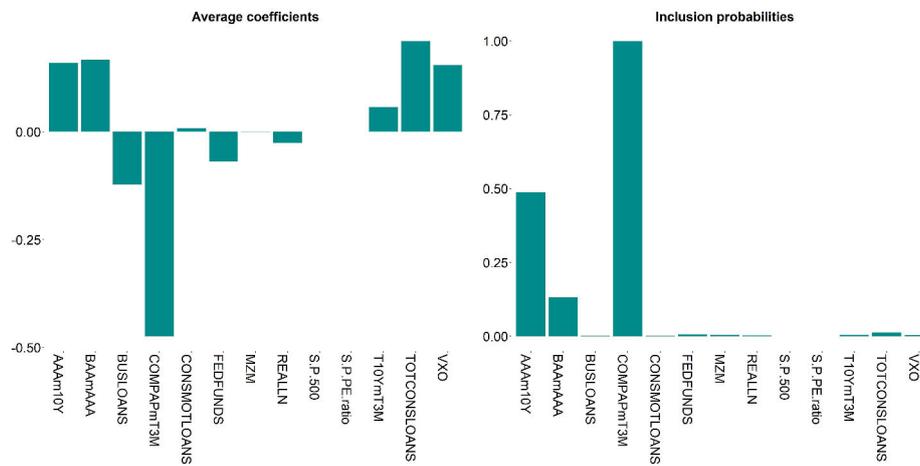


(c) $h=3$

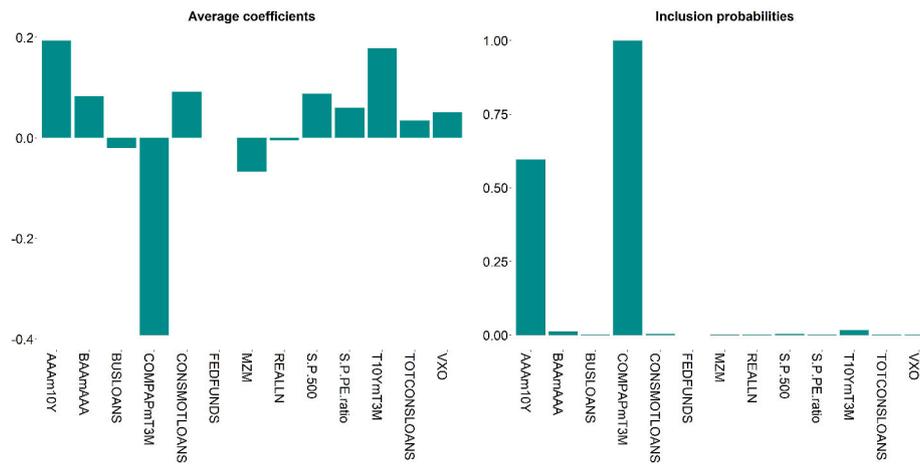
Figure C.2: BSTS importance statistics



(a) $h=4$



(b) $h=5$



(c) $h=6$

Figure C.3: Elastic Net importance statistics

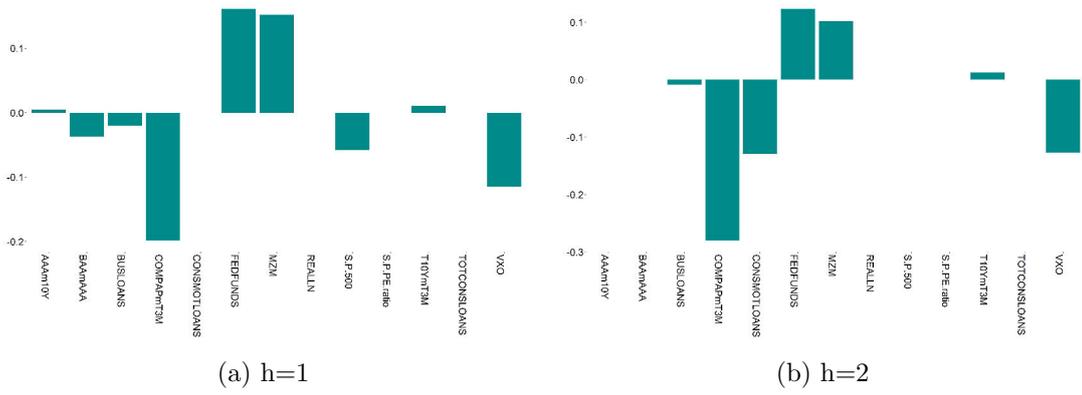


Figure C.4: Elastic Net importance statistics

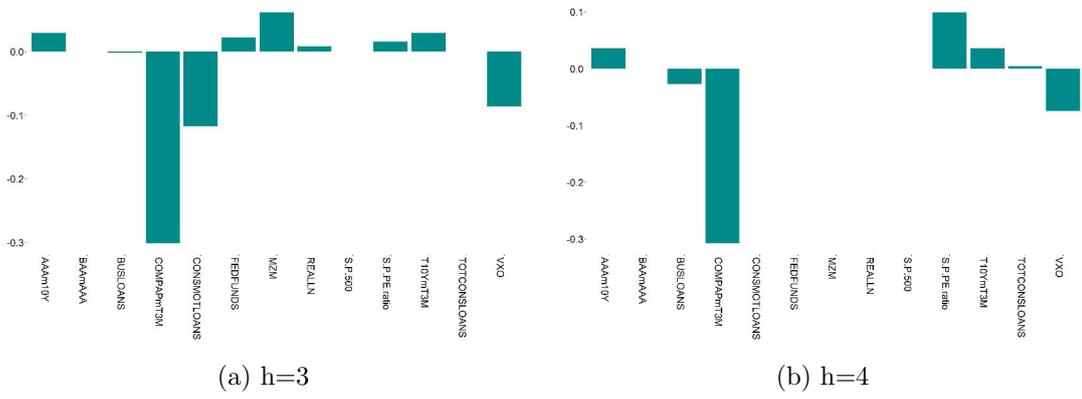


Figure C.5: Elastic Net importance statistics

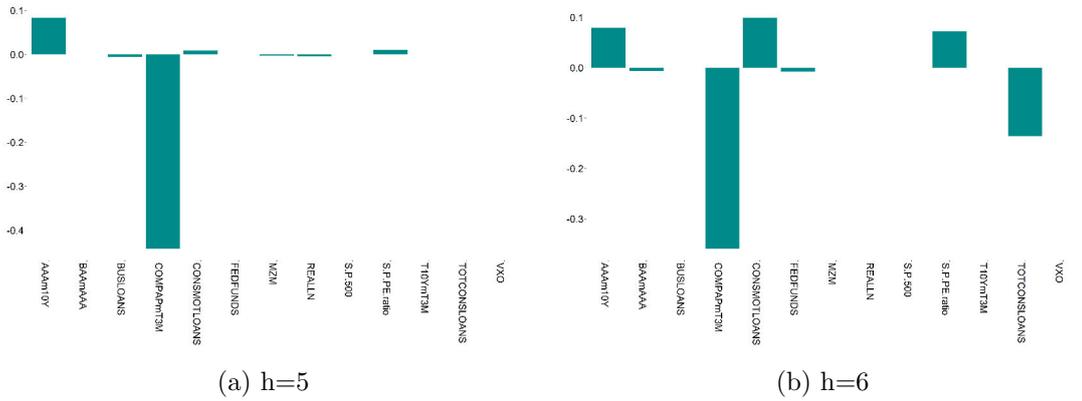


Figure C.6: Random Forest importance statistics

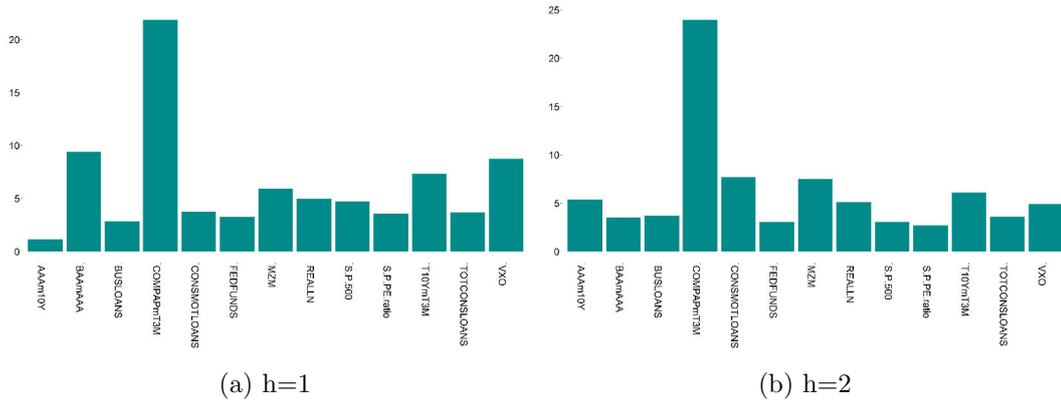


Figure C.7: Random Forest importance statistics

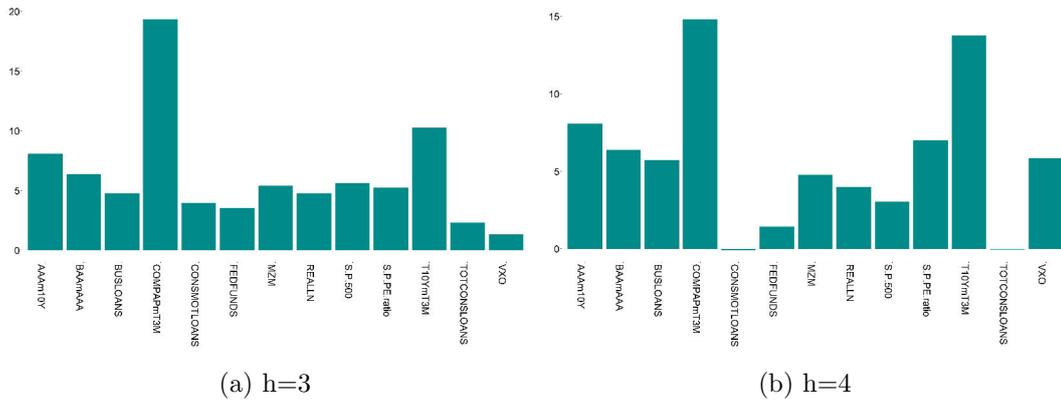


Figure C.8: Random Forest importance statistics

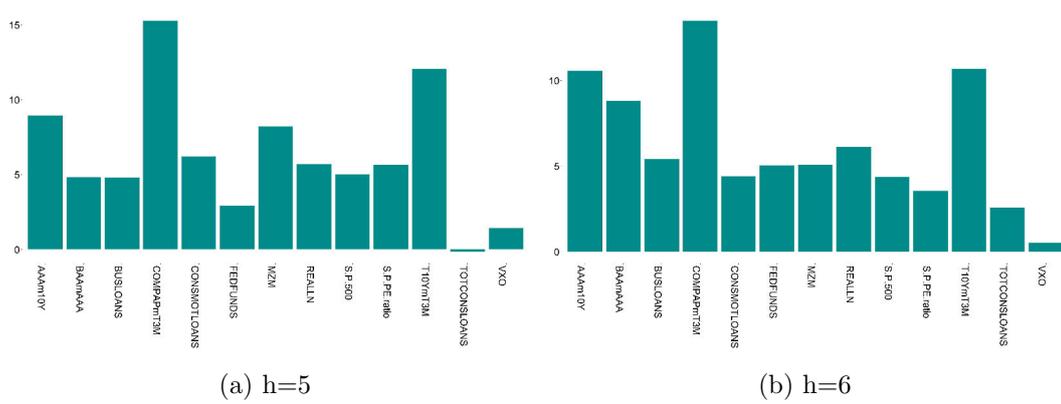


Figure C.9: Neural Network importance statistics

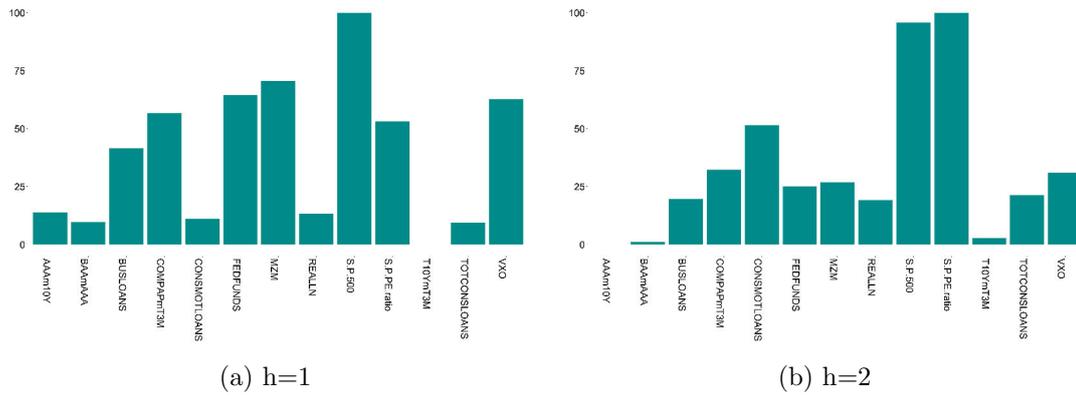


Figure C.10: Neural Network importance statistics

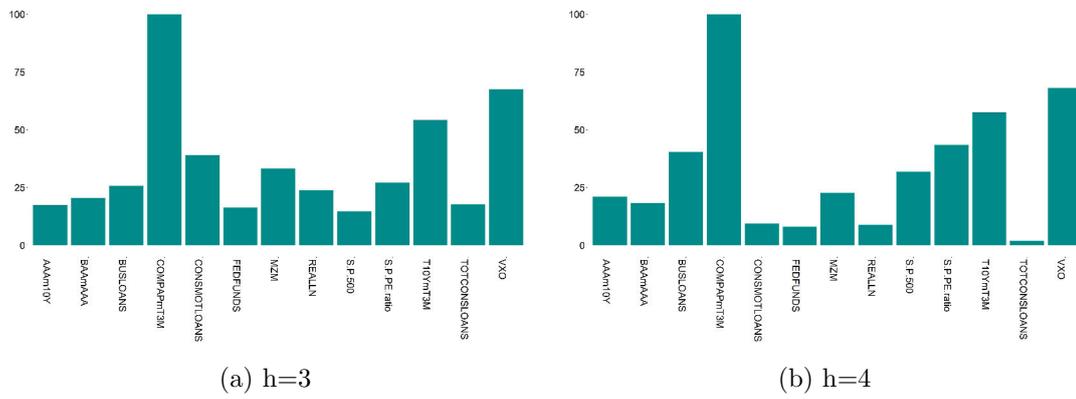


Figure C.11: Neural Network importance statistics

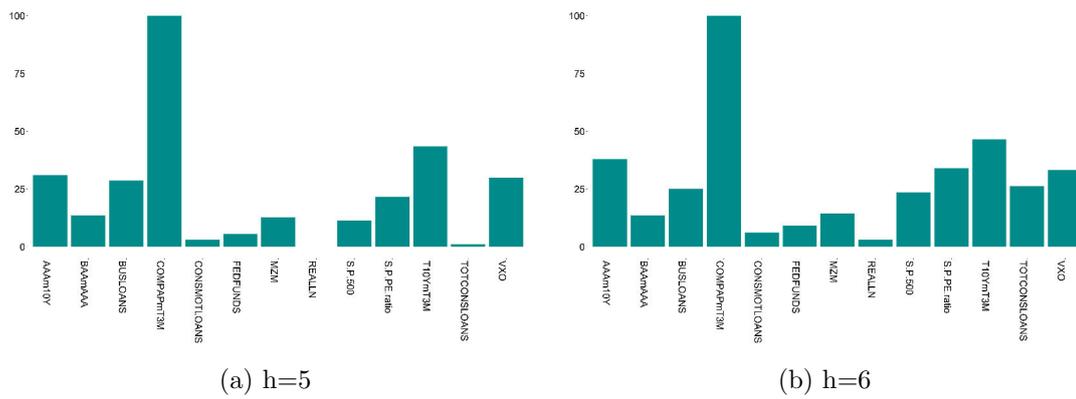
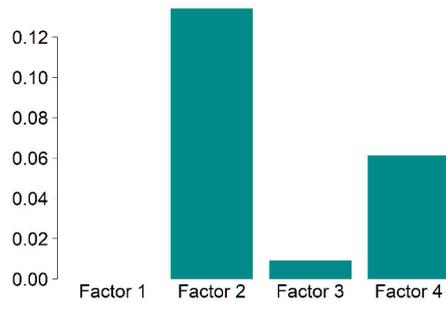
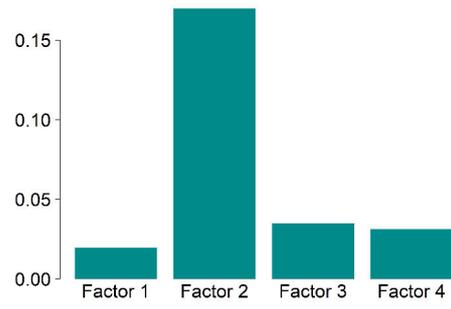


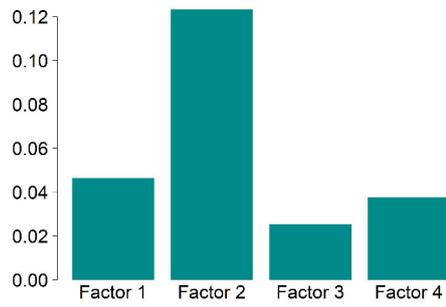
Figure C.12: FADL importance statistics



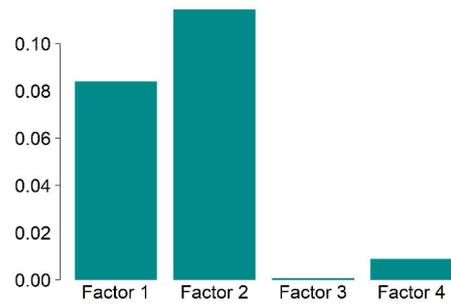
(a) $h=1$



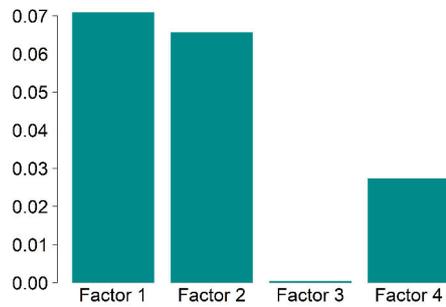
(b) $h=2$



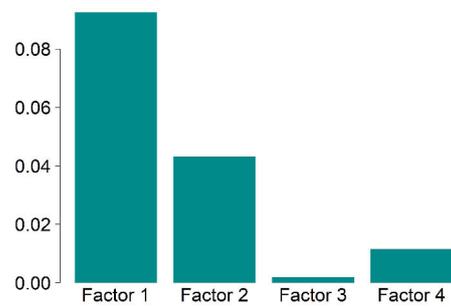
(c) $h=3$



(d) $h=4$



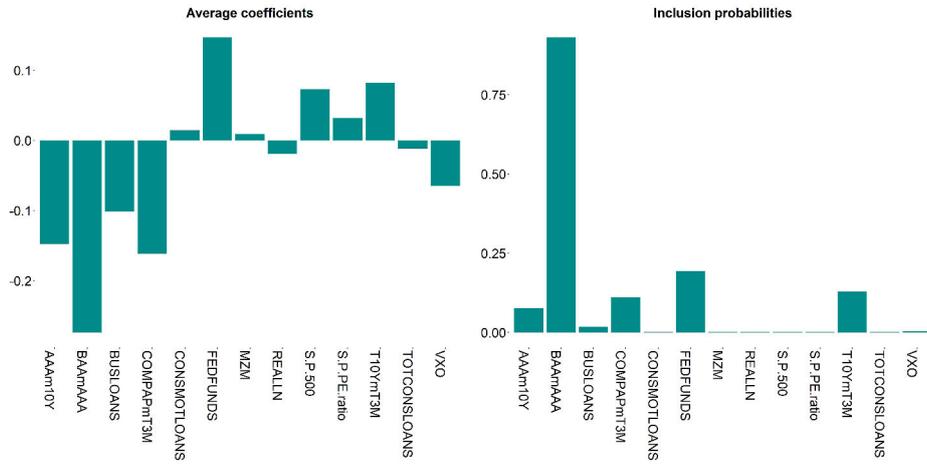
(e) $h=5$



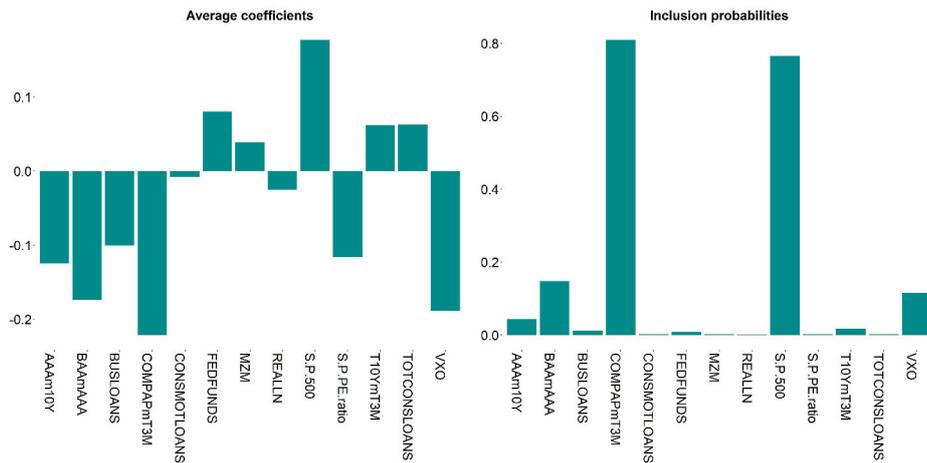
(f) $h=6$

C.3.2 Period 2

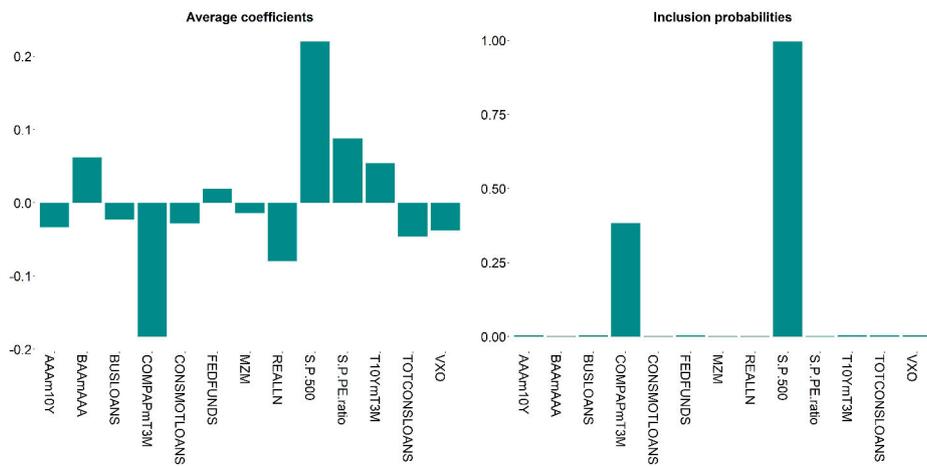
Figure C.13: BSTS importance statistics



(a) $h=1$

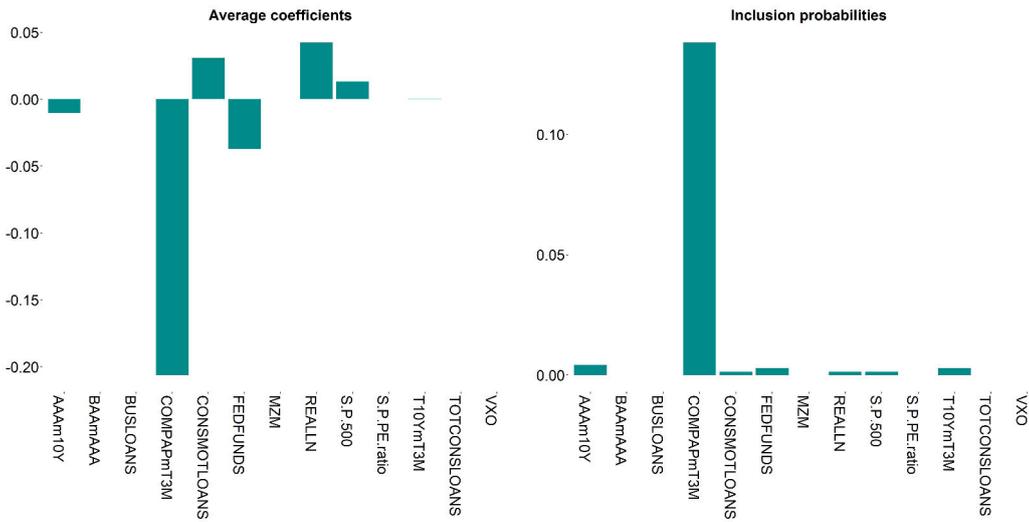


(b) $h=2$

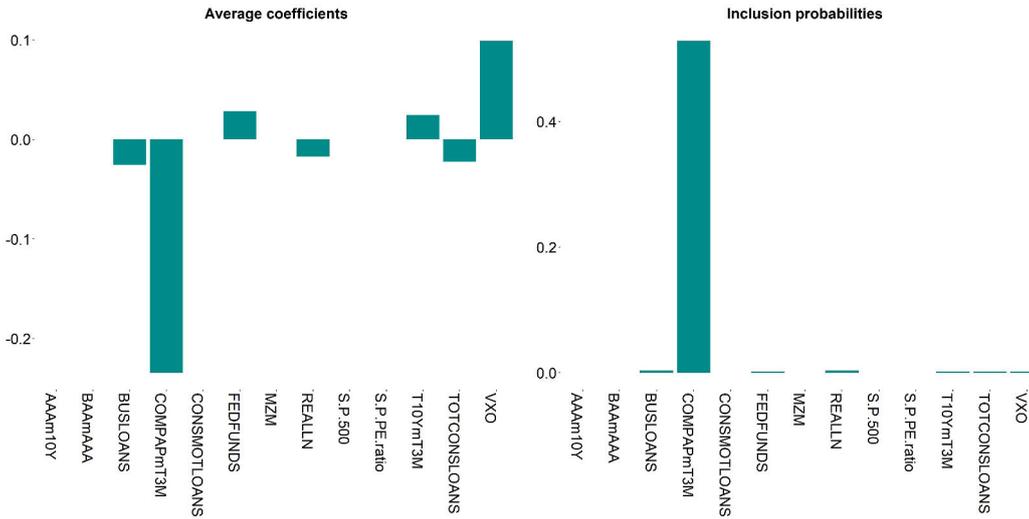


(c) $h=3$

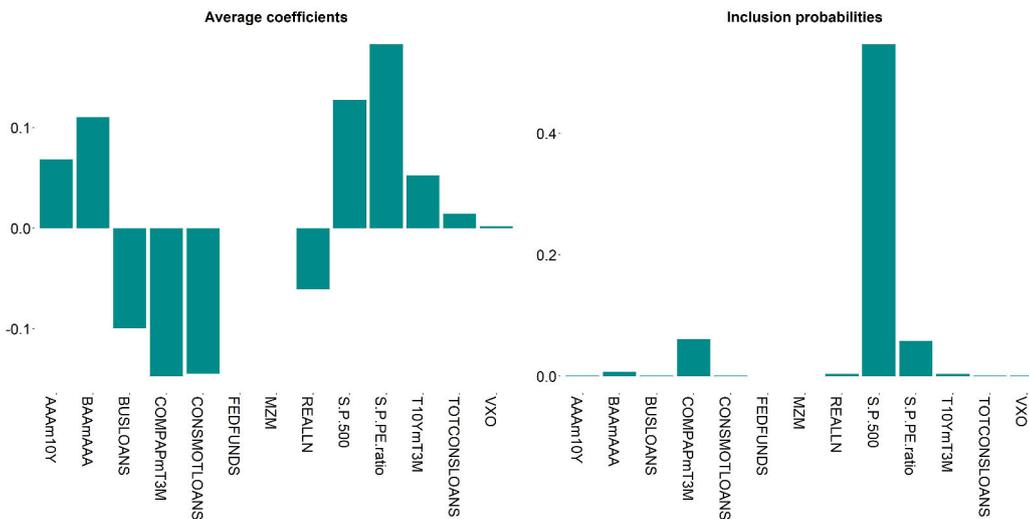
Figure C.14: BSTS importance statistics



(a) $h=4$



(b) $h=5$



(c) $h=6$

Figure C.15: Elastic Net importance statistics

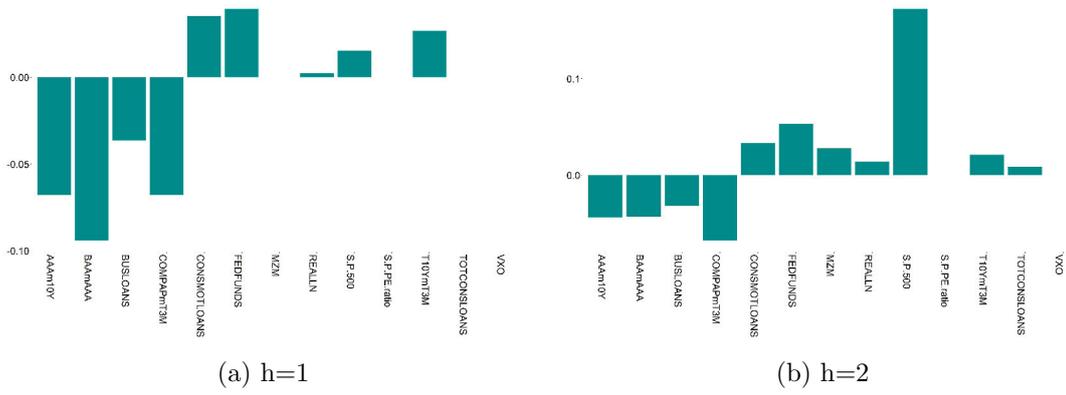


Figure C.16: Elastic Net importance statistics

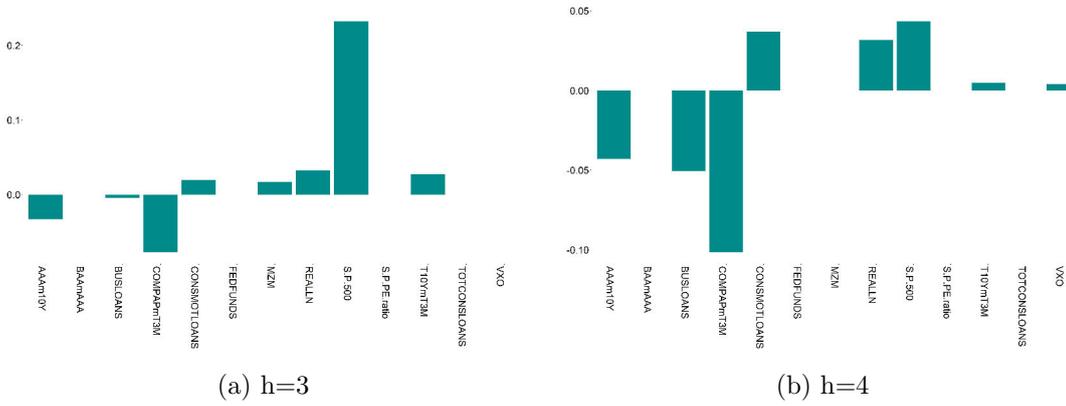


Figure C.17: Elastic Net importance statistics

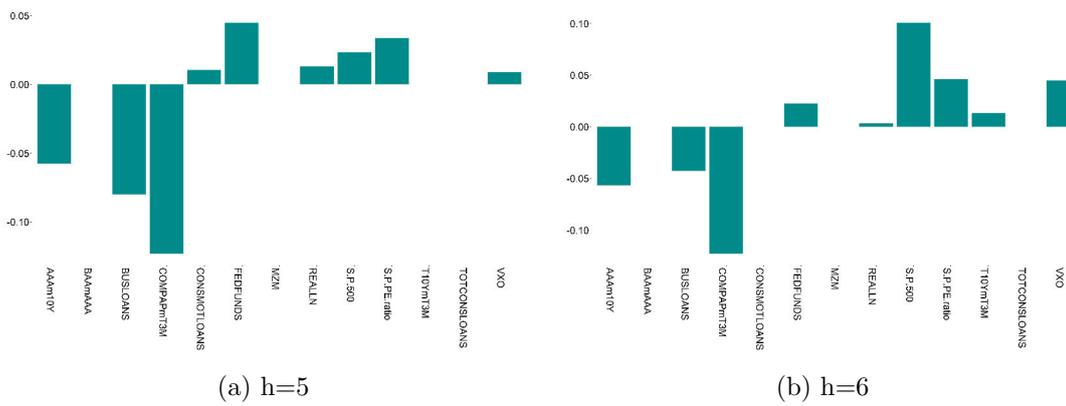


Figure C.18: Random Forest importance statistics

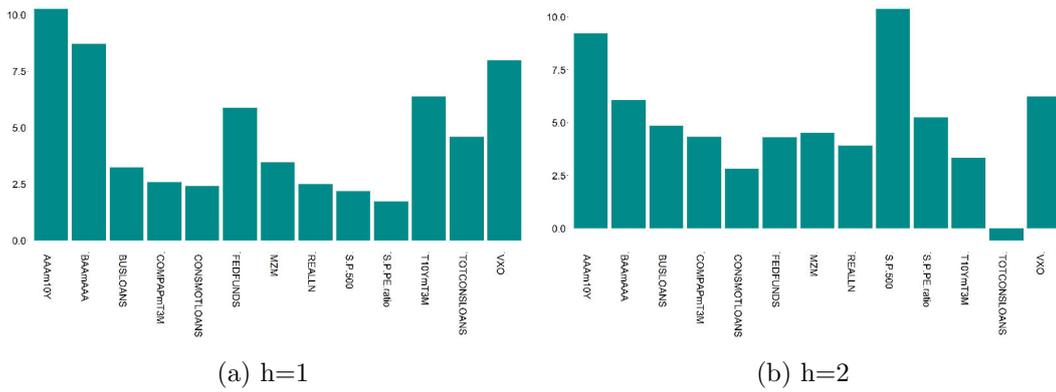


Figure C.19: Random Forest importance statistics

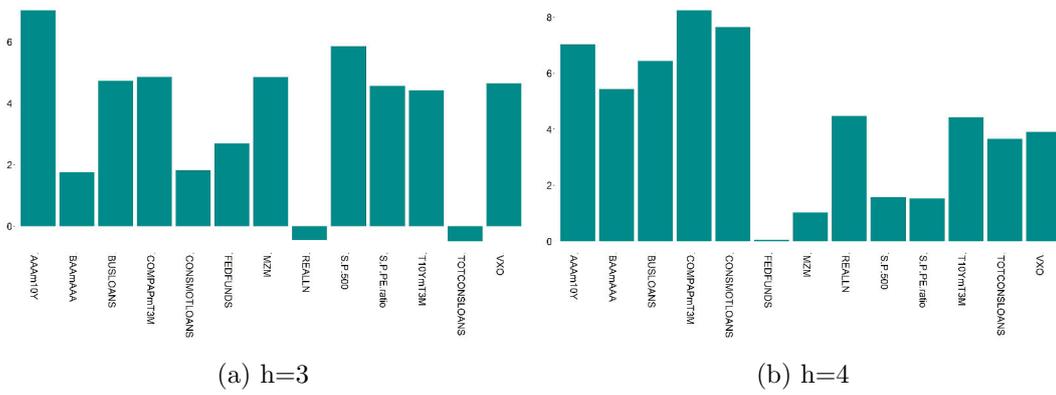


Figure C.20: Random Forest importance statistics

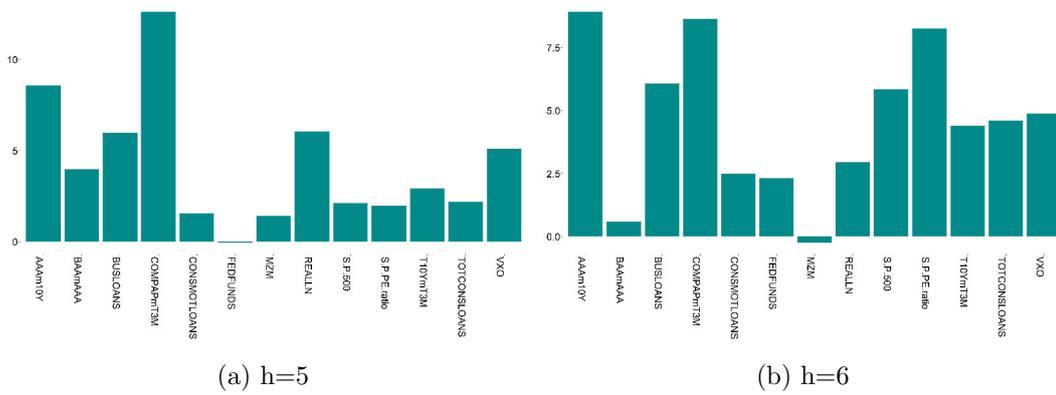


Figure C.21: Neural Network importance statistics

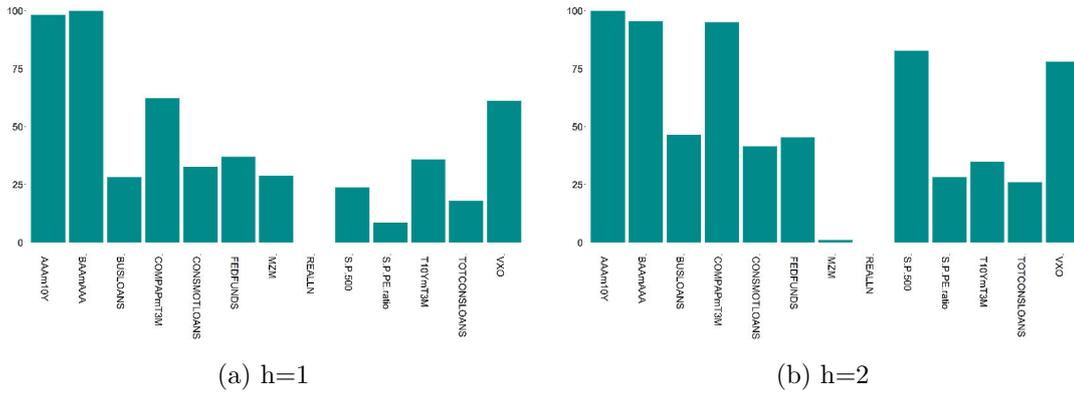


Figure C.22: Neural Network importance statistics

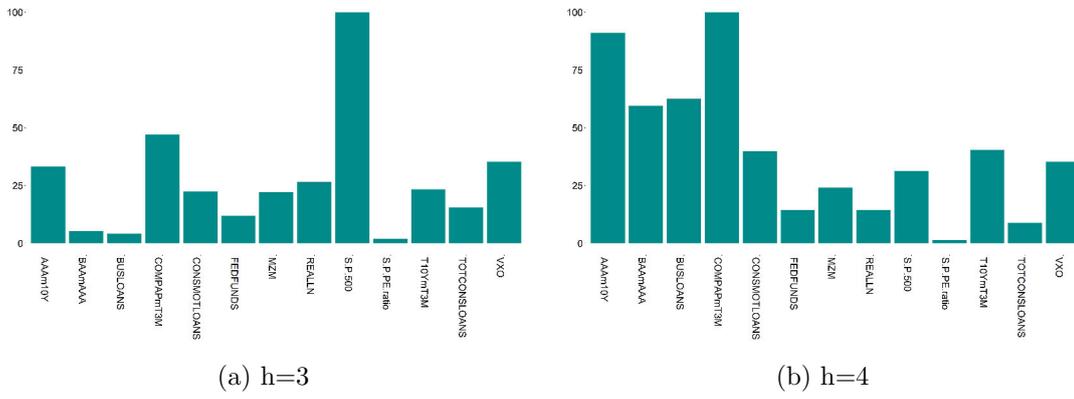


Figure C.23: Neural Network importance statistics

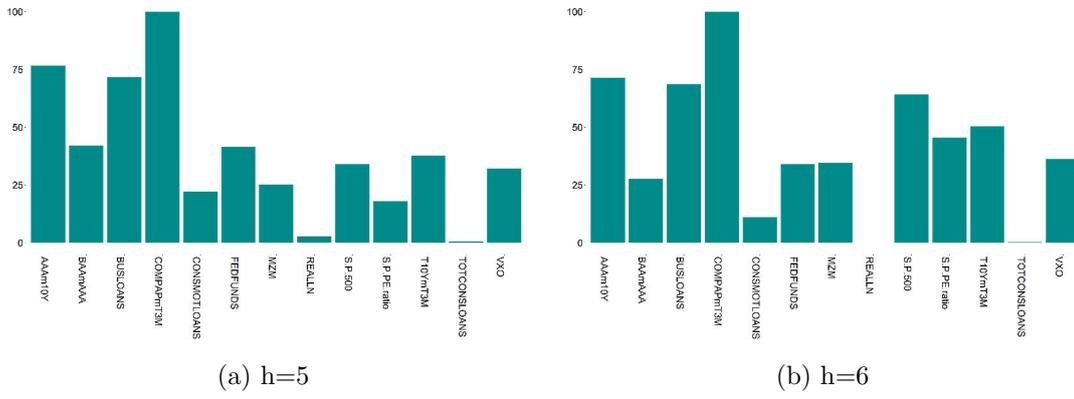
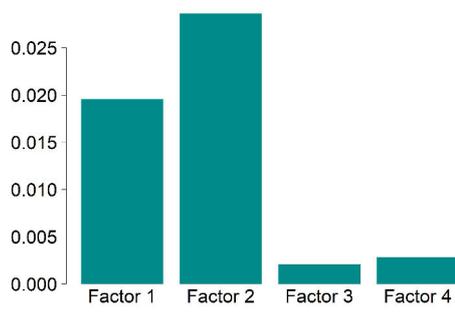
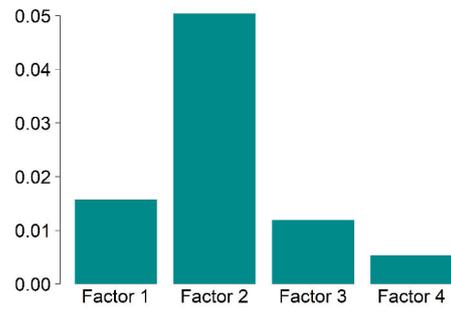


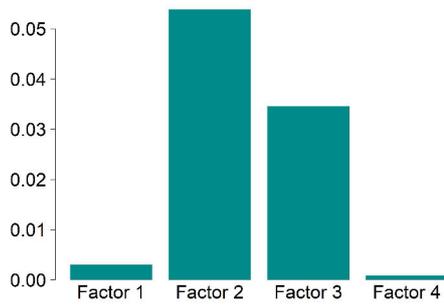
Figure C.24: FADL importance statistics



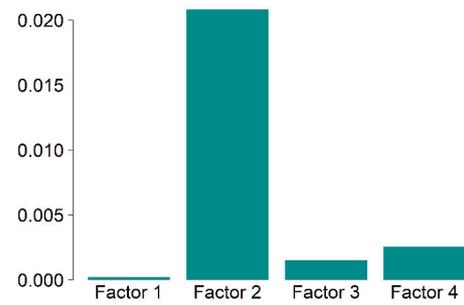
(a) $h=1$



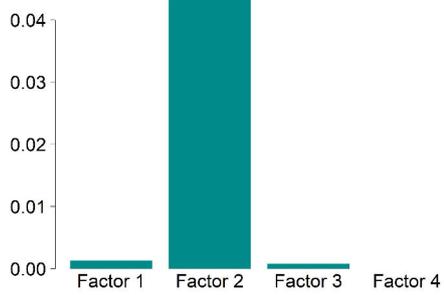
(b) $h=2$



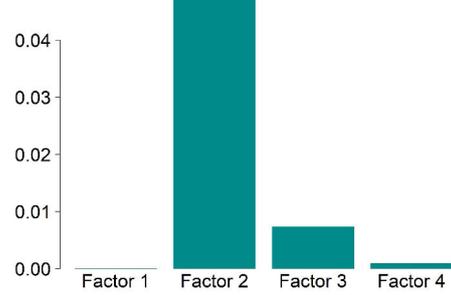
(c) $h=3$



(d) $h=4$



(e) $h=5$



(f) $h=6$

General Conclusion

In this thesis, I have tried to contribute to a better understanding of the interplay between the financial sector and the real economy, a far cry from conventional stereotypes and prejudices about finance. First, I emphasized the prominence of a careful and balanced appraisal of the mechanisms underlying macro-financial linkages. In this respect, the most recent financial episodes are of paramount importance. Macro-financial linkages are not perfectly understood because their measurement is inherently fraught with pitfalls, which impedes our ability to monitor them. An additional source of complexity is that financial frictions, which underlie macro-financial linkages, wax and wane with the Business Cycle, but may also fluctuate autonomously.

My first contribution is to propose a methodology for the measurement of the Financial Cycle. I claim that the Financial Cycle should be decomposed into a Credit Cycle and a Financial Condition Cycle, these two components affecting economic activity differently and at distinct frequencies. Because the estimation of macro-financial linkages is complicated in normal times, my estimation of the two components is grounded on specific events in which financial frictions culminate.

As another contribution, complementary to the previous one, the thesis confirms that financial shocks are important sources of Business Cycle fluctuations. Given the lack of guidance of theoretical models on the recursive ordering between financial and economic variables, I used an agnostic data-driven technique to uncover the dynamic lead-lag relationship between economic and financial variables. Overall, I found that the ordering suggested by the algorithm is stable across countries, but different from that of previous work.

Finally, the thesis explores the unstable predictive power of financial variables. The findings reinforce the view that financial variables have lost relevance for forecasting economic outcomes, despite lower macroeconomic volatility and enhanced financial market structure. However, financial variables should not be systematically discarded and more flexible forecasting models should instead be considered.

Overall, the thesis confirms that any modern macroeconomic analysis cannot proceed without explicit reference to financial factors. Financial factors are helpful to signal both macroeconomic and financial imbalances, either owing to causal or forward-looking relationships.

These contributions notwithstanding, the thesis makes it clear that there is still ample room for a better understanding of the real impact of financial factors. The first avenue for future research relates to the interaction between credit and financial conditions, insofar as the maximal distortion for economic activity may arise when the two head in the same direction and interact. The second is that structural models should allow for an asymmetric response of the economy to positive and negative financial shocks. The third is to better understand whether the predictive power of financial variables and its consequent instability bears upon causal or forward-looking factors, which would definitely enhance our ability to use these variables to anticipate the Business Cycle.

Turning to policy implications, the main thrust of the thesis is that central banks and macroprudential authorities alike should put as much energy in measuring and monitoring the Financial Cycle as with respect to the Business Cycle. Moreover, to the extent that the management of financial frictions is very complicated once a financial crisis has erupted, the Financial Cycle should be tamed right from the onset. Because forecasting financial crisis is inherently difficult, the prevailing compromise between type I and type II errors should perhaps be revisited in favor of the latter, even though this entails a cost for short-term growth.

An additional challenge in this direction is that macroeconomic research should adapt to an ever-changing financial system, chiefly owing to changes in the conduct of monetary policy, the low interest rate environment and the rise of non-bank financial intermediaries. The Great Financial Crisis has forced modern central banks to engage in unconventional monetary policies that will most likely become the norm. As a result, central banks now respond to and have leeway on, a broader set of financial conditions than the sole policy rate. The subsequent structural change in macro-financial linkages is potentially of the same magnitude as that of the 1980s. As a consequence, the estimation of macro-financial models should, as much as possible, be confined to the most recent period.

In this respect, the broad-based expansion of financial data fueled by the Great Financial Crisis can be of great help, with the caveat that it takes purposeful analysis to identify financial data with a strong signal-to-noise ratio. In particular, economists should keep in mind that in the two polar cases of excessively low volatility and heightened financial stress, the signal provided by financial variables can be highly misleading. As a consequence, the way we look at financial data should itself be state-dependent.

Bibliography

- D. Acemoglu and J. Robinson. *Why nations fail: The origins of power, prosperity, and poverty*. Broadway Business, 2013.
- V. Acharya and L. Pedersen. Asset pricing with liquidity risk. *Journal of financial Economics*, 77(2):375–410, 2005.
- V. Acharya and S. Steffen. The “greatest” carry trade ever? Understanding eurozone bank risks. *Journal of Financial Economics*, 115(2):215–236, 2015.
- V. Acharya, M. Richardson, S. van Nieuwerburgh, and L. White. Guaranteed to Fail: Fannie Mae, Freddie Mac and the Debacle of Mortgage Finance. *Princeton University Press*, 2011.
- M. Adelino, A. Schoar, and F. Severino. House prices, collateral, and self-employment. *Journal of Financial Economics*, 117(2):288–306, 2015.
- M. Adelino, A. Schoar, and F. Severino. Loan originations and defaults in the mortgage crisis: The role of the middle class. *The Review of Financial Studies*, 29(7):1635–1670, 2016.
- T. Adrian and N. Boyarchenko. Intermediary Leverage Cycles and Financial Stability. *Federal Reserve Bank of New York Staff Report*, 567, 2012.
- T. Adrian and N. Liang. Monetary Policy, Financial Conditions, and Financial Stability. *Federal Reserve Bank of New York Staff Report*, 690, 2016.
- T. Adrian and H. Shin. Liquidity and leverage. *Journal of Financial Intermediation*, 19(3):418–437, 2006.
- T. Adrian and H. Shin. Financial intermediaries, financial stability and monetary policy. *Federal Reserve Bank of Kansas City Symposium at Jackson Hole*, August 2008a.
- T. Adrian and H. Shin. Financial intermediary leverage and value-at-risk. *Staff Report, Federal Reserve Bank of New York*, 2008b.
- T. Adrian and H. Shin. Financial intermediaries and monetary economics. *B. Friedman and M. Woodford (eds) Handbook of Monetary Economics*, 3:601–650, 2010a.
- T. Adrian and H. Shin. The Changing Nature of Financial Intermediation and Financial Crisis of 2007-2009. *Annual Review of Economics*, pages 603–618, 2010b.
- T. Adrian, E. Moench, and H. Shin. Macro risk premium and intermediary balance sheet quantities. *Federal Reserve Bank of New York Staff Reports*, 428, 2010.

- T. Adrian, A. Ashcraft, H. Boesky, and Z. Pozsar. Shadow banking. *Federal Reserve Bank of New York Economic Policy Review Google Scholar*, 2013a.
- T. Adrian, P. Collat, and H. Shin. Which Financial Frictions: Parsing the Evidence from the Financial Crisis of 2007 to 2009. *NBER Macroeconomics Annual*, 27:159–214, 2013b.
- T. Adrian, F. Grinberg, N. Liang, and S. Malik. *The term structure of growth-at-risk*. International Monetary Fund, 2018.
- M. Aglietta. Les crises financières: plus ça change, plus c’est la même chose. *Revue d’économie financière*, pages 39–45, 2008.
- D. Aikman, A. Haldane, and B. Nelson. Curbing the credit cycle. *Economic Journal*, 125: 1072–1109, 2015.
- D. Aikman, A. Haldane, M. Hinterschweiger, and S. Kapadia. Rethinking financial stability. *Forthcoming*, 2018.
- G. Akerlof. The market for lemons: Qualitative uncertainty and the market mechanism. *Quarterly Journal of Economics*, 84(3), 1970.
- E. Alberola, Á. Estrada, and D. Santabárbara. Growth Beyond imbalances: Sustainable growth rates and output gap reassessment. *Banco de España Working Papers*, 1313, 2013.
- E. Alberola, Á. Estrada, and D. Santabárbara. Growth and Imbalances in Spain: A Reassessment of the Output Gap. *Journal of the Spanish Economic Association*, 5(2-3):333–356, 2014.
- G. Allen and R. Fildes. Econometric forecasting. In *Principles of forecasting*, pages 303–362. Springer, 2001.
- H. Almeida, M. Campello, and C. Liu. The financial accelerator: Evidence from international housing markets. *Review of Finance*, 10(3):321–352, 2006.
- M. Andersson and S. Karlsson. Bayesian forecast combination for VAR models. In *Bayesian econometrics*, pages 501–524. Emerald Group Publishing Limited, 2008.
- A. Ando and F. Modigliani. The ‘life cycle’ hypothesis of saving: Aggregate implications and tests. *American Economic Review*, 53(1):55–84, 1963.
- E. Andreou, D. Osborn, and M. Sensier. A comparison of the statistical properties of financial variables in the USA, UK and Germany over the business cycle. *The Manchester School*, 68(4):396–418, 2000.
- A. Ang, M. Piazzesi, and M. Wei. What does the yield curve tell us about GDP growth? *Journal of Econometrics*, 131:359–403, 2006.
- E. Angelopoulou, H. Balfoussia, and H. Gibson. Building a financial conditions index for the euro area and selected euro area countries: what does it tell us about the crisis? *Economic Modelling*, 38:392–403, 2014.

- C. Arellano and E. Mendoza. Credit frictions and 'sudden stops' in small open economies: An equilibrium business cycle framework for emerging markets crises. *National Bureau of Economic Research*, 2002.
- S. Arora, B. Barak, M. Brunnermeier, and R. Ge. Computational complexity and information asymmetry in financial products. *Working paper*, 2009.
- K. Arrow. Optimal capital policy, the cost of capital, and myopic decision rules. *Annals of the Institute of Statistical Mathematics*, 16(1):21–30, 1964.
- K. Arrow and G. Debreu. Existence of an equilibrium for a competitive economy. *Econometrica: Journal of the Econometric Society*, pages 265–290, 1954.
- P. Asea and B. Blomberg. Lending cycles. *Journal of Econometrics*, 83(1-2):89–128, 1998.
- A. Ashcraft, T. Schuermann, et al. Understanding the securitization of subprime mortgage credit. *Foundations and Trends[®] in Finance*, 2(3):191–309, 2008.
- K. Assenmacher-Wesche and S. Gerlach. Monetary policy, credit and asset prices: facts and fiction. *Economic Policy*, 25(63):437–482, 2010.
- C. Azariadis. Credit cycles and business cycles. *Federal Reserve Bank of St. Louis*, 100(1):45–71, 2018.
- J. Babecký, T. Havranek, J. Mateju, M. Rusnák, K. Smidkova, and B. Vasicek. Banking, debt and currency crises: early warning indicators for developed countries. *European Central Bank Working Paper Series*, 1485, 2012.
- W. Bagehot. *Lombard Street: A description of the money market*. Scribner, Armstrong & Company, 1873.
- F. C. Bagliano and C. Morana. The great recession: Us dynamics and spillovers to the world economy. *Journal of Banking & Finance*, 36(1):1–13, 2012.
- J. Bai and S. Ng. Determining the number of factors in approximate factor models. *Econometrica*, 70(1):191–221, 2002.
- J. Bai and S. Ng. Determining the number of primitive shocks in factor models. *Journal of Business & Economic Statistics*, 25(1):52–60, 2007.
- D. Baker. Blame it on the bubble. *The Guardian*, March 8, 2010.
- M. Baker, J. Stein, and J. Wurgler. When does the market matter? Stock prices and the investment of equity-dependent firms. *The Quarterly Journal of Economics*, 118(3):969–1005, 2003.
- S. Baker and N. Bloom. Does Uncertainty Reduce Growth? Using Disasters as Natural Experiments. *NBER Working Paper*, 19475, 2013.
- M. Bańbura and G. Rünstler. A look into the factor model black box: publication lags and the role of hard and soft data in forecasting gdp. *International Journal of Forecasting*, 27(2):333–346, 2011.

- M. Banbura, D. Giannone, and L. Reichlin. Large Bayesian Vector Autoregressions. *Journal of Applied Econometrics*, 25(1):71–92, 2010.
- A. Banerjee and E. Duflo. Growth theory through the lens of development economics. *Handbook of economic growth*, 1:473–552, 2005.
- R. Banerjee and B. Hofmann. The rise of zombie firms: causes and consequences. *BIS Quarterly Review September*, 2018.
- R. Barro. Rare disasters and asset markets in the twentieth century. *The Quarterly Journal of Economics*, 121(3):823–866, 2006.
- R. Barsky and J. De Long. Why does the stock market fluctuate? *Quarterly Journal of Economics*, 108(2):291–311, 1993.
- R. Barsky and E. Sims. Information, animal spirits, and the meaning of innovations in consumer confidence. *NBER Working Paper*, 15049, 2008.
- S. Barthelemy and T. Apoteker. Genetic algorithms and financial crises in emerging markets. *Working Paper*, 2000.
- A. Basistha. Trend-cycle correlation, drift break and the estimation of trend and cycle in Canadian GDP. *Canadian Journal of Economics/Revue canadienne d'économique*, 40(2): 584–606, 2007.
- J. Baskin and P. Miranti. A History of Corporate Finance. *Cambridge University Press*, 1997.
- S. Basu and J. Fernald. What do we know (and not know) about potential output? *Federal Reserve Bank of St. Louis Review*, July - August 2009.
- S. Battistion, D. Delli Gatti, M. Gallegati, B. Greenwald, and J. Stiglitz. Liaisons dangereuses: increasing connectivity, risk sharing and systemic risk. *Journal of Economic Dynamics and Control*, 36(8):1121–1141, 2012.
- M. Baxter and R. King. Measuring business cycles: approximate band-pass filters for economic time series. *Review of economics and statistics*, 81(4):575–593, 1999.
- T. Bayoumi and A. Swiston. Foreign entanglements: measuring the size and source of spillovers across industrial countries. *IMF Working Paper*, 07(182), 2007.
- K. Beaton, R. Lalonde, and C. Luu. A financial conditions index for the united states. Technical report, Bank of Canada Discussion Paper, 2009.
- P. Beaudry and F. Portier. Stock prices, news, and economic fluctuations. *American Economic Review*, pages 1293–1307, 2006.
- T. Beck, B. Büyükkarabacak, F. Rioja, and N. Valev. Who gets the credit? And does it matter? Household vs. firm lending across countries. *The BE Journal of Macroeconomics*, 12(1), 2012.

- B. Benanke and M. Gertler. Agency costs, net worth, and business fluctuation. *American Economic Review*, 79(1):14–31, 1989.
- J. Benes, M. Johnson, K. Clinton, T. Matheson, P. Manchev, R. Garcia-Saltos, and D. Laxton. Estimating Potential Output with a Multivariate Filter. *IMF Working Papers*, 10/285, 2010.
- P. Bennett, S. Peristiani, et al. Are US reserve requirements still binding? *Federal Reserve Bank of New York Economic Policy Review*, 8(1):53–68, 2002.
- T. Berge. Predicting recessions with leading indicators: Model averaging and selection over the business cycle. *Journal of Forecasting*, 34(6):455–471, 2015.
- H. Berger, T. Dowling, S. Lanau, W. Lian, M. Mrkaic, P. Rabanal, and M. Taheri Sanjani. Steady as She Goes: Estimating Potential Output During Financial Booms and Busts. *IMF Working Papers*, 15/233, 2015.
- C. Bergmeir and J. Benítez. On the use of cross-validation for time series predictor evaluation. *Information Sciences*, 191:192–213, 2012.
- B. Bernanke. Non-monetary effects of the financial crisis in the propagation of the Great Depression. *National Bureau of Economic Research*, 1983.
- B. Bernanke. On the predictive power of interest rates and interest rate spreads. *National Bureau of Economic Research*, 1990.
- B. Bernanke and A. Gertler. Inside the black box: the credit channel of monetary transmission. *Journal of Economic Perspectives*, 9(4):27–48, 1995.
- B. Bernanke and M. Gertler. Should central banks respond to movements in asset prices? *American Economic Review*, 91(2):253–257, 2001.
- B. Bernanke and I. Mihov. Measuring monetary policy. *The Quarterly Journal of Economics*, 113(3):869–902, 1998.
- B. Bernanke, M. Gertler, and S. Gilchrist. The Financial Accelerator in a Quantitative Business Cycle Framework. *John B. Taylor and Michael Woodford (eds.), Handbook of macroeconomics*, 1C:1341–1393, 1999.
- B. Bernanke et al. Credit in the macroeconomy. *Quarterly Review-Federal Reserve Bank of New York*, 18:50–50, 1993.
- B. Bernanke et al. The financial accelerator and the credit channel. Technical report, Board of Governors of the Federal Reserve System (U.S.), 2007.
- H. Bernard and S. Gerlach. Does the term structure predict recessions? The international evidence. *International Journal of Finance & Economics*, 3(3):195–215, 1998.
- M. Bertrand, A. Schoar, and D. Thesmar. Banking deregulation and industry structure: Evidence from the French banking reforms of 1985. *The Journal of Finance*, 62(2):597–628, 2007.

- S. Beveridge and C. Nelson. A new approach to decomposition of economic time series into permanent and transitory components with particular attention to measurement of the ‘business cycle’. *Journal of Monetary economics*, 7(2):151–174, 1981.
- R. Bhansali. Asymptotically efficient autoregressive model selection for multistep prediction. *Annals of the Institute of Statistical Mathematics*, 48(3):577–602, 1996.
- R. Bhansali. Direct autoregressive predictors for multistep prediction: Order selection and performance relative to the plug in predictors. *Statistica Sinica*, pages 425–449, 1997.
- O. Blanchard and J. Simon. The long and large decline in US output volatility. *Brookings papers on economic activity*, 2001(1):135–164, 2001.
- O. Blanchard and M. Watson. Bubbles, rational expectations and financial markets. *National Bureau of economic research*, 1982.
- O. Blanchard, C. Rhee, and L. Summers. The stock market, profit, and investment. *The Quarterly Journal of Economics*, 108(1):115–136, 1993.
- O. Blanchard, J.-P. L’Huillier, and G. Lorenzoni. News, noise, and fluctuations: an empirical exploration. *NBER Working Paper*, 15015, 2009.
- O. Blanchard et al. Output, the stock market, and interest rates. *American Economic Review*, 71(1):132–143, 1981.
- A. Blinder. Two bubbles, two paths. *The New York Times*, June 15th 2008.
- N. Bloom. The impact of uncertainty shocks. *Econometrica*, 77(3):623–85, 2009.
- N. Bloom. Fluctuations in uncertainty. *Journal of Economic Perspectives*, 28(2):153–76, 2014.
- A. Blum, A. Kalai, and J. Langford. Beating the hold-out: Bounds for k-fold and progressive cross-validation. In *Proceedings of the twelfth annual conference on Computational learning theory*, pages 203–208. ACM, 1999.
- J. Boivin and S. Ng. Are More Data Always Better for Factor Analysis? *Journal of Econometrics*, 132:169–194, 2006.
- L. Boone. *An assessment of trend extraction techniques: application to time series decomposition of business cycle and endogenous technical progress*. PhD thesis, London Business School (University of London), 1995.
- L. Boone. Comparing semi-structural methods to estimate unobserved variables. *OECD Working Papers*, 240, 2000.
- M. Bordo and J. Haubrich. The yield curve, recessions and the credibility of the monetary regime: Long run evidence 1875-1997. *National Bureau of Economic Research*, 2004.
- C. Borio. The financial cycle and macroeconomics: What have we learnt? *Journal of Banking & Finance*, 45:182–198, 2014.

- C. Borio and P. Disyatat. Global imbalances and the financial crisis: Link or no link? *BIS Working Paper*, 346, 2011.
- C. Borio and M. Drehmann. Assessing the risk of banking crises—revisited. *BIS Quarterly Review*, March, 2009.
- C. Borio and P. Lowe. Asset prices, financial and monetary stability: exploring the nexus. *BIS Working Paper*, 114, 2002.
- C. Borio and P. Lowe. Securing sustainable price stability: should credit come back from the wilderness? *BIS Working Paper*, 157, 2004.
- C. Borio and H. Zhu. Capital regulation, risk-taking and monetary policy: a missing link in the transmission mechanism? *BIS Working Papers*, 268, December 2011.
- C. Borio, M. Drehmann, L. Gambacorta, G. Jiménez, and C. Trucharte. Countercyclical capital buffers: exploring options. *BIS Working Paper*, 2010.
- C. Borio, M. Drehmann, and K. Tsatsaronis. Characterising the financial cycle: Don't lose sight of the medium term! *BIS Working Papers*, 380, 2012.
- C. Borio, P. Disyatat, and M. Juselius. A parsimonious approach to incorporating economic information in measures of potential output. *BIS Working Paper*, 442, 2014.
- C. Borio, P. Disyatat, and M. Juselius. Rethinking potential output: Embedding information about the financial cycle. *Oxford Economic Papers*, 69(3):655–677, 2016.
- G. Box and G. Jenkins. Time series analysis, forecasting, and control. *Francisco Holden-Day*, 1970.
- E. Boz and E. Mendoza. Financial innovation, the discovery of risk and the U.S. credit crisis. *Journal of Monetary Economics*, 62:1–22, 2014.
- P. Brandt and J. Freeman. Advances in Bayesian Time Series Modeling and the Study of Politics: Theory Testing, Forecasting, and Policy Analysis. *Political Analysis*, 2006.
- S. Brave and A. Butters. Diagnosing the Financial System: Financial Conditions and Financial Stress. *International Journal of Central Banking*, 8:191–239, 2012.
- S. Brave and R. Butters. Monitoring financial stability: A financial conditions index approach. *Federal Reserve Bank of Chicago*, Issue Q I:22–43, 2011.
- A. Bredahl Kock and T. Teräsvirta. Forecasting macroeconomic variables using neural network models and three automated model selection techniques. *Econometric Reviews*, 35 (8-10):1753–1779, 2016.
- M. Brunnermeier. Deciphering the 2007-08 Liquidity and Credit Crunch. *Journal of Economic Perspective*, 23(1):77–100, 2009.
- M. Brunnermeier and L. Pedersen. Funding liquidity and market liquidity. *Review of Financial Studies*, 22(2201-2238):6, 2009.

- M. Brunnermeier and Y. Sannikov. A macroeconomic model with a financial sector. *American Economic Review*, 104(2):379–421, 2014.
- M. Brunnermeier, C. Gollier, and J. Parker. Optimal beliefs, asset prices, and the preference for skewed returns. *American Economic Review*, 97(2):159–165, 2007.
- M. Brunnermeier, T. Eisenbach, and Y. Sannikov. Macroeconomics with Financial Frictions: A Survey. *Advances in Economics and Econometrics: Tenth World Congress of the Econometric Society*, 2:3–94, 2013.
- G. Bry and C. Boschan. Cyclical analysis of time series: Selected procedures and computer programs. *NBER Technical Paper*, 20, 1971.
- C. Buch, J. Doepke, and K. Stahn. Great moderation at the firm level? Unconditional vs. conditional output volatility. *The BE Journal of Economic Analysis & Policy*, 9(1), 2009.
- W. H. Buiter. Housing wealth isn't wealth. *National Bureau of Economic Research*, 2008.
- C. Burnside, M. Eichenbaum, and S. Rebelo. Prospective deficits and the asian currency crisis. *Journal of political Economy*, 109(6):1155–1197, 2001.
- R. Caballero and E. Farhi. On the role of safe asset shortages in secular stagnation. *Secular stagnation: Facts, causes and cures*, page 111, 2014.
- R. Caballero, E. Farhi, and P.-O. Gourinchas. An equilibrium model of global imbalances and low interest rates. *American Economic Review*, 98(1):358–393, 2008a.
- R. Caballero, T. Hoshi, and A. Kashyap. Zombie lending and depressed restructuring in Japan. *American Economic Review*, 98:1943–1977, 2008b.
- R. Caballero, E. Farhi, and P.-O. Gourinchas. Safe asset scarcity and aggregate demand. *American Economic Review*, 106(5):513–18, 2016.
- R. Caballero, E. Farhi, and P.-O. Gourinchas. The safe assets shortage conundrum. *Journal of Economic Perspectives*, 31(3):29–46, 2017.
- G. Calvo, L. Leiderman, and C. Reinhart. Inflows of capital to developing countries in the 1990s. *Journal of economic perspectives*, 10(2):123–139, 1996.
- A. Calza, T. Monacelli, and L. Stracca. Housing finance and monetary policy. *Journal of the European Economic Association*, 2011.
- M. Camacho, G. Perez-Quiros, and P. Poncela. Green shoots in the euro area: a real time measure. *Banco de Espana Working Paper*, 1026, 2010.
- M. Camacho, G. Perez-Quiros, and P. Poncela. Markov-switching dynamic factor models in real time. *International Journal of Forecasting*, 34(4):598–611, 2018.
- J. Campbell. Asset prices, consumption, and the business cycle. *Handbook of macroeconomics*, 1:1231–1303, 1999.

- J. Campbell and J. Cochrane. By force of habit: A consumption-based explanation of aggregate stock market behavior. *Journal of political Economy*, 107(2):205–251, 1999.
- J. Campbell, A. Lo, A. MacKinlay, et al. *The econometrics of financial markets*, volume 2. Princeton University press, 1997.
- F. Canova. Methods for applied macroeconomic research. *Princeton University Press*, 2011.
- F. Canova and M. Ciccarelli. Panel Vector Autoregressive Models: A Survey. In *VAR Models in Macroeconomics—New Developments and Applications: Essays in Honor of Christopher A. Sims*. Emerald Group Publishing Limited, pages 205–246, 2013.
- F. Canova and L. Gambetti. Structural changes in the US economy: Bad Luck or Bad Policy? *CEPR Discussion Papers*, 5457, 2006.
- F. Canova and E. Pappa. Price Differentials in Monetary Unions: The Role of Fiscal Shocks. *Economic Journal*, 117(520):713–737, 2007.
- F. Canova and M. Paustian. Credit cycles redux. *International Economic Review*, 45(4): 1011–1046, 2004.
- F. Canova and M. Paustian. The financial accelerator in an estimated New Keynesian model. *Review of Economic Dynamics*, 11:155–178, 2008.
- F. Canova and M. Paustian. Business cycle measurement with some theory. *Journal of Monetary Economics*, 58:345–361, 2011.
- G. Caprio and D. Klingebiel. Episodes of systemic and borderline financial crisis. *World Bank Mimeo*, January, 2003.
- M. Carlson, H. Shan, and M. Warusawitharana. Capital ratios and bank lending: A matched bank approach. *Journal of Financial Intermediation*, 22(4):663–687, 2013.
- C. Carlstrom and T. Fuerst. Agency costs, net worth, and business fluctuations: A computable general equilibrium analysis. *The American Economic Review*, pages 893–910, 1997.
- C. Carroll, M. Otsuka, and J. Slacalek. How large are housing and financial wealth effects? A new approach. *Journal of Money, Credit and Banking*, 43(1):55–79, 2011.
- K. Case and R. Shiller. Is there a bubble in the housing market? *Brookings papers on economic activity*, 2003(2):299–342, 2003.
- S. Catherine, T. Chaney, Z. Huang, D. Sraer, and D. Thesmar. Aggregate effects of collateral constraints. *Working paper*, 2017.
- P. Catte, N. Girouard, R. Price, and C. André. Housing markets, wealth and the business cycle. *OECD Publishing*, 2004.
- S. Cecchetti. Measuring the macroeconomic risks posed by asset price booms. In *Asset prices and monetary policy*, pages 9–43. University of Chicago Press, 2008.

- S. Cecchetti and E. Kharroubi. Reassessing the impact of finance on growth. *BIS Working Paper*, 381, 2012.
- S. Cecchetti and E. Kharroubi. Why does financial sector growth crowd out real economic growth? *BIS Working Paper*, 490, 2015.
- S. Cecchetti, A. Flores-Lagunes, and S. Krause. Assessing the sources of changes in the volatility of real growth. Technical report, National Bureau of Economic Research, 2006.
- S. Cecchetti, M. Kohler, and C. Upper. Financial crises and economic activity. Technical report, National Bureau of Economic Research, 2009.
- V. Cerra and S. Saxena. Growth dynamics: the myth of economic recovery. *American Economic Review*, 98(1):439–57, 2008.
- I. Chakraborty, I. Goldstein, and A. MacKinlay. Monetary stimulus and bank lending. *Journal of Financial Economics*, 2017.
- V. Chari, L. Christiano, P. Kehoe, et al. Facts and myths about the financial crisis of 2008. *Federal Reserve Bank of Minneapolis Working Paper*, 666, 2008.
- M. Chauvet. An econometric characterization of business cycle dynamics with factor structure and regime switching. *International economic review*, pages 969–996, 1998.
- M. Chauvet and J. Hamilton. Dating business cycle turning points. In *Nonlinear time series analysis of business cycles*, pages 1–54. Emerald Group Publishing Limited, 2006.
- M. Chauvet and S. Potter. Recent changes in the us business cycle. *The Manchester School*, 69(5):481–508, 2001.
- M. Chauvet and S. Potter. Forecasting output. In *Handbook of Economic Forecasting*, volume 2, pages 141–194. Elsevier, 2013.
- S. Chen and R. Ranciere. Financial information and macroeconomic forecasts. *International Journal of Forecasting*, 2019.
- R. Chirinko, L. De Haan, and E. Sterken. Asset price shocks, real expenditures, and financial structure: a multi-country analysis. *DNB Working Papers*, 014, 2008.
- G. Chodorow-Reich and A. Falato. The loan covenant channel: How bank health transmits to the real economy. *National Bureau of Economic Research*, 2017.
- Y. Chong and D. Hendry. Econometric evaluation of linear macro-economic models. *The Review of Economic Studies*, 53(4):671–690, 1986.
- L. Christiano and T. Fitzgerald. The Bandpass filter. *International Economic Review*, 44(2): 435–465, 2003.
- L. Christiano, M. Eichenbaum, and C. Evans. Monetary policy shocks: What have we learned and to what end? *Handbook of macroeconomics*, 1:65–148, 1999.

- L. Christiano, R. Motto, and M. Rostagno. Risk Shocks. *American Economic Review*, 104(1):27–65, 2014.
- L. Christiano, M. Eichenbaum, and M. Trabandt. Understanding the Great Recession. *American Economic Journal: Macroeconomics*, 7(1):110–67, 2015.
- M. Ciccarelli, E. Ortega, and M. Valderrama. Heterogeneity and cross-country spillovers in macroeconomic-financial linkages. *Banco de España Working Papers*, 1241, 2012.
- S. Claessens, M. Kose, and M. Terrones. Financial cycles: What? How? When? *IMF Working Paper*, 11/76, 2011.
- S. Claessens, M. Kose, and M. Terrones. How do business and financial cycles interact? *Journal of International Economics*, 87:178–190, 2012.
- R. Clarida, J. Gali, and M. Gertler. Monetary policy rules and macroeconomic stability: evidence and some theory. *The Quarterly journal of economics*, 115(1):147–180, 2000.
- P. Clark. The cyclical component of US economic activity. *Quarterly Journal of Economics*, 102(4):797–814, 1987.
- P. Clark. Trend reversion in real output and unemployment. *Journal of Econometrics*, 40(1):15–32, 1989.
- T. Clark and M. McCracken. Averaging forecasts from VARs with uncertain instabilities. *Journal of Applied Econometrics*, 25(1):5–29, 2010.
- M. Clements and D. Hendry. Forecasting economic processes. *International Journal of Forecasting*, 14(1):111–131, 1998.
- M. Clements and D. Hendry. On winning forecasting competitions in economics. *Spanish Economic Review*, 1(2):123–160, 1999.
- M. Clements and D. Hendry. *Forecasting non-stationary economic time series*. MIT Press, 2001.
- J. Cochrane. Permanent and transitory components of GNP and stock prices. *The Quarterly Journal of Economics*, 109(1):241–265, 1994.
- J. Cochrane. *Asset Pricing*. Princeton University Press, 2001.
- N. Coimbra and H. Rey. Financial cycles with heterogeneous intermediaries. Technical report, National Bureau of Economic Research, 2017.
- R. Cole. Front matter to “errors in provisional estimates of gross national product”. In *Errors in Provisional Estimates of Gross National Product*, pages 15–0. NBER, 1969.
- P. Comon. Independent component analysis, a new concept? *Signal processing*, 36(3):287–314, 1994.
- G. M. Constantinides and D. Duffie. Asset pricing with heterogeneous consumers. *Journal of Political economy*, 104(2):219–240, 1996.

- T. Cook and T. Hahn. The effect of changes in the federal funds rate target on market interest rates in the 1970s. *Journal of Monetary Economics*, 24(3):331–351, 1989.
- T. Cook and A. Hall. Macroeconomic Indicator Forecasting with Deep Neural Networks. *Federal Reserve Bank of Kansas City, Research Working Paper*, 17(11), 2017.
- J. Coval, J. Jurek, and E. Stafford. The Economics of Structured Finance. *Journal of Economic Perspective*, 23(1):3–25, 2009.
- D. Cox. Prediction by exponentially weighted moving averages and related methods. *Journal of the Royal Statistical Society. Series B (Methodological)*, pages 414–422, 1961.
- V. Curdia and M. Woodford. Credit spreads and monetary policy. *Journal of Money, Credit and Banking*, 42(6):3–35, 2010.
- M. Darracq-Paries, L. Maurin, and D. Moccero. Financial conditions index and credit supply shocks for the euro area. *European Central Bank Working Paper Series*, 1644, 2014.
- Z. Darvas and A. Simon. Filling the gap: open economy considerations for more reliable potential output estimates. *Bruegel Working Papers*, 10401, 2015.
- W. De Bondt and R. Thaler. Does the Stock Market Overreact? *Journal of Finance*, 40(3):793–805, 1985.
- W. De Bondt and R. Thaler. Further Evidence on Investor Overreaction and Stock Market Seasonality. *Journal of Finance*, 42(3):557–581, 1987.
- G. Debreu. *Theory of Value An Axiomatic Analysis of Economic Equilibrium*. Cowles Foundation Yale University, 1959.
- M. Del Negro and F. Schorfheide. Bayesian macroeconometrics, 2011.
- M. Del Negro and F. Schorfheide. Forecasting with DSGE models: theory and practice. *Handbook of forecasting*, 2, 2012.
- M. Del Negro and F. Schorfheide. DSGE model-based forecasting. In *Handbook of economic forecasting*, volume 2, pages 57–140. Elsevier, 2013.
- M. Del Negro, G. Eggertsson, A. Ferrero, and N. Kiyotaki. The great escape? A quantitative evaluation of the Fed’s liquidity facilities. *American Economic Review*, 107(3):824–857, 2011.
- A. Dempster, N. Laird, and D. Rubin. Maximum likelihood from incomplete data via the EM algorithm. *Journal of the royal statistical society. Series B (methodological)*, pages 1–38, 1977.
- E. Detragiache and A. Spilimbergo. *Crises and liquidity: evidence and interpretation*, volume 1-2. International Monetary Fund, 2001.
- M. Devereux and A. Sutherland. A portfolio model of capital flows to emerging markets. *Journal of Development Economics*, 89(2):181–93, 2009.

- M. Devereux and A. Sutherland. Country portfolio dynamics. *Journal of Economic Dynamics and Control*, 34(7):1325–42, 2010.
- M. Devereux and C. Yu. International financial integration and crisis contagion. Technical report, National Bureau of Economic Research, 2014.
- M. Devereux, P. Lane, and J. Xu. Exchange rates and monetary policy in emerging market economies. *Economic Journal*, 116(511):478–506, 2006.
- F. Di Mauro, F. Fornari, and D. Mannucci. Stock market firm-level information and real economic activity. *European Central Bank Working Paper Series*, 1366, 2011.
- D. Diamond and P. Dybvig. Bank Runs, Deposit Insurance, and Liquidity. *Journal of Political Economy*, 91(3):401–419, 1983.
- D. Dias, C. Marques, and C. Richmond. Misallocation and productivity in the lead up to the Eurozone crisis. *Journal of Macroeconomics*, 49:46–70, 2016.
- F. Diebold. Forecast combination and encompassing: Reconciling two divergent literatures. *International Journal of Forecasting*, 5(4):589–592, 1989.
- F. Diebold and R. Mariano. Comparing Predictive Accuracy. *Journal of Business & Economic Statistics*, 20(1):134–144, 2002.
- F. Diebold and K. Yilmaz. Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal*, 119(534):158–71, 2009.
- F. Diebold and K. Yilmaz. Financial and macroeconomic connectedness: A network approach to measurement and monitoring. *Oxford University Press*, 2015.
- F. Diebold, G. Rudebusch, et al. Does the business cycle have duration memory? Technical report, Board of Governors of the Federal Reserve System (US), 1987.
- F. Diebold, J.-H. Lee, and G. Weinbach. Regime switching with time-varying transition probabilities. *Business Cycles: Durations, Dynamics, and Forecasting*, 1:144–165, 1994.
- F. Diebold, M. Piazzesi, and G. Rudebusch. Modeling bond yields in finance and macroeconomics. *American Economic Review*, 95(2):415–20, 2005.
- F. Diebold, G. Rudebusch, and S. Aruoba. The macroeconomy and the yield curve: A dynamic latent factor approach. *Journal of Econometrics*, 131(1-2):309–38, 2006.
- A. Dixit and J. Stiglitz. Monopolistic competition and optimum product diversity. *The American Economic Review*, 67(3):297–308, 1977.
- T. Doan, R. Litterman, and C. Sims. Forecasting and conditional projection using realistic prior distributions. *Econometric reviews*, 3(1):1–100, 1984.
- D. Domanski, T. Ng, et al. Getting effective macroprudential policy on the road: eight propositions. *BIS papers*, 1:89, 2011.

- M. Drehmann and M. Juselius. Measuring liquidity constraints in the economy: the debt service ratio and financial crises. *BIS Quarterly Review*, pages 21–35, September 2012.
- M. Drehmann, A. Illes, M. Juselius, and M. Santos. How much income is used for debt payments? A new database for debt service ratios. *BIS Quarterly Review*, September 2015.
- M. Drehmann, M. Juselius, and A. Korinek. Accounting for Debt Service : The Painful Legacy of Credit Booms. *BIS Working Papers*, 645, 2017.
- P. Dubey, J. Geanakoplos, and M. Shubik. Default and punishment in general equilibrium. *Econometrica*, 73(1):1–37, 2005.
- J. Duca, J. Muellbauer, and A. Murphy. Shifting credit standards and the boom and bust in us house prices. *Federal Reserve Bank of Dallas Working Papers*, 1104, 2011.
- N. Dunbar. The devil’s derivatives. *Boston, MA: HBS*, 2011.
- A. Duncan and C. Nolan. Disputes, debt and equity. *SSRN 3069639*, 2017.
- J. Durbin and S. Koopman. Time series analysis by state space methods. *Oxford University Press*, 2012.
- J. Durbin and S.-J. Koopman. A simple and efficient simulation smoother for state space time series analysis. *Biometrika*, 89(3):603–616, 2002.
- G. Dwyer and P. Tkac. The financial crisis of 2008 in fixed-income markets. *Journal of International Money and Finance*, 28(8):1293–1316, 2009.
- K. Dynan, D. Elmendorf, and D. Sichel. Can financial innovation help to explain the reduced volatility of economic activity? *Journal of monetary Economics*, 53(1):123–150, 2006.
- O. Eckstein and A. Sinai. The mechanisms of the business cycle in the postwar era. In *The American business cycle: Continuity and change*, pages 39–122. University of Chicago Press, 1986.
- G. Eggertsson and P. Krugman. Debt, Deleveraging, and Liquidity Trap: A Fisher-Minsky-Koo Approach. *Quarterly Journal of Economics*, 127(3):1469–1513, 2012.
- G. Eggertsson and M. Woodford. The zero interest-rate bound and optimal monetary policy. *Brookings Papers on Economic Activity*, 1:139–211, 2003.
- W. English, K. Tsatsaronis, and E. Zoli. Assessing the predictive power of measures of financial conditions for macroeconomic variables. *BIS Working Papers*, 22:228–252, 2005.
- L. Epstein and S. Zin. Substitution, risk aversion and the temporal behavior of consumption and asset returns: A theoretical framework. *Econometrica*, 57(4):937–969, 1989.
- R. Espinoza, F. Fornari, and M. Lombardi. The role of financial variables in predicting economic activity. *Journal of Forecasting*, 31(1):15–46, 2012.

- A. Estrella. Why does the yield curve predict output and inflation? *Economic Journal*, 115: 722–44, 2005.
- A. Estrella and G. Hardouvelis. The term structure as a predictor of real economic activity. *Journal of Finance*, 46(2):555–76, 1991.
- A. Estrella and F. Mishkin. The Predictive Power of the Term Structure of Interest Rates in Europe and the United States: Implications for the European Central Bank. *European Economic Review*, 41(7):1375–401, 1997.
- A. Estrella and F. Mishkin. Predicting U.S. Recessions: Financial Variables As Leading Indicators. *Review of Economics and Statistics*, 80(1):45–61, 1998.
- A. Estrella and M. Trubin. The yield curve as a leading indicator: Some practical issues. *Current Issues in Economics and Finance*, 12(5), 2006.
- A. Estrella, A. Rodrigues, and S. Schich. How stable is the predictive power of the yield curve? Evidence from Germany and the United States. *Review of Economics and Statistics*, 85(3):629–644, 2003.
- E. Fama. Stock returns, real activity, inflation, and money. *The American economic review*, 71(4):545–565, 1981.
- R. Farmer. Confidence, crashes and animal spirits. *NBER Working Paper*, 14846, 2009.
- J. Faust and J. Wright. Forecasting inflation. In *Handbook of economic forecasting*, volume 2, pages 2–56. Elsevier, 2013.
- S. Fazzari, G. Hubbard, and B. Petersen. Investment, financing decisions, and tax policy. *The American Economic Review*, 78(2):200–205, 1988.
- L. Ferrara, M. Marcellino, and M. Mogliani. Macroeconomic forecasting during the great recession: The return of non-linearity? *International Journal of Forecasting*, 31(3):664–679, 2015.
- R. Fildes and K. Ord. Forecasting competitions—their role in improving forecasting practice and research. *A companion to economic forecasting*, pages 322–353, 2002.
- R. Fildes and H. Stekler. The state of macroeconomic forecasting. *Journal of Macroeconomics*, 24(4):435–468, 2002.
- D. Findley. On the use of multiple models for multi-period forecasting. In *Proceedings of Business and Economic Statistics, American Statistical Association*, pages 528–531, 1983.
- I. Fisher. Booms and depressions. *New York, Adelphi Co.*, 1932.
- I. Fisher. The Debt-Deflation Theory of Great Depressions. *Econometrica*, 1(4):337–357, 1933.
- R. Fisman and I. Love. Financial dependence and growth revisited. *Journal of the European Economic Association*, 5(2-3):470–479, 2007.

- F. Fornari and L. Stracca. What does a financial shock do? First international evidence. *Economic Policy*, 27(71):407–445, 2013.
- M. Forni and L. Gambetti. Sufficient information in structural vars. *Journal of Monetary Economics*, 66:124–136, 2014.
- J. Frankel and A. Rose. Currency crashes in emerging markets: An empirical treatment. *Journal of international Economics*, 41(3-4):351–366, 1996.
- J. Frankel and S.-J. Wei. Managing macroeconomic crises. Technical report, National Bureau of Economic Research, 2004.
- B. Friedman and K. Kuttner. Money, income and prices after the 1980s. *National Bureau of Economic Research*, 1989.
- M. Friedman. Introduction to “A Theory of the Consumption Function”. In *A theory of the consumption function*, pages 1–6. Princeton university press, 1957.
- M. Friedman and A. Schwartz. A Monetary History of the United States, 1867-1960. *Princeton University Press for the National Bureau of Economic Research*, 1963.
- R. Fry and A. Pagan. Sign Restrictions in Structural Vector Autoregressions: A Critical Review. *NCER Working Paper Series*, 57, 2010.
- H. Fuchi, I. Muto, and H. Ugai. A historical evaluation of financial accelerator effects in Japan’s economy. *Bank of Japan Working Paper Series*, 05-E-8, 2005.
- F. Furlanetto, P. Gelain, and M. Taheri Sanjani. Output Gap in Presence of Financial Frictions and Monetary Policy Trade-offs. *IMF Working Papers*, 14/128, 2014.
- X. Gabaix. Variable rare disasters: An exactly solved framework for ten puzzles in macro-finance. *The Quarterly journal of economics*, 127(2):645–700, 2012.
- G. Galati, I. Hindrayanto, S.-J. Koopman, and M. Vlekke. Measuring financial cycles in a model-based analysis: Empirical evidence for the United States and the euro area. *Economics Letters*, 145:83–87, 2016.
- A. Galvão and M. Owyang. Measuring macro-financial conditions using a factor-augmented smooth-transition vector autoregression. Technical report, Mimeo, 2013.
- L. Gambetti and A. Musso. Loan supply shocks and the business cycle. *Journal of Applied Econometrics*, 32(4):764–782, 2017.
- L. Gambetti, E. Pappa, and F. Canova. The structural dynamics of US output and inflation: what explains the changes? *Journal of Money, Credit and Banking*, 40(2-3):369–388, 2008.
- D. Garson. Interpreting neural-network connection weights. *AI Expert*, 6(4):46–51, 1991.
- C. Gauthier, C. Graham, and Y. Liu. Financial conditions indices for canada. *Bank of Canada. Photocopy*, 2003.

- W. Gavin and A. Theodorou. A common model approach to macroeconomics: using panel data to reduce sampling error. *Journal of Forecasting*, 24(3):203–219, 2005.
- J. Geanakoplos. The Leverage Cycle. *NBER Macroeconomics Annual*, 24, 2010.
- E. George and R. McCulloch. Approaches for Bayesian variable selection. *Statistica sinica*, pages 339–373, 1997.
- A. Gerali, S. Neri, L. Sessa, and F. Signoretti. Credit and Banking in a DSGE Model of the Euro Area. *Journal of Money, Credit and Banking*, 42:107–141, 2010.
- M. Gertler. Financial structure and aggregate economic activity: An overview. *Journal of Money, Credit, and Banking*, 20:559–588, 1988.
- M. Gertler and S. Gilchrist. What Happened: Financial Factors in the Great Recession. *Journal of Economic Perspectives*, 32(3):3–30, 2018.
- M. Gertler and N. Kiyotaki. Financial intermediation and credit policy in business cycle analysis. In *Handbook of monetary economics*, volume 3, pages 547–599. Elsevier, 2010.
- M. Gertler and N. Kiyotaki. Banking, liquidity, and bank runs in an infinite horizon economy. *American Economic Review*, 105(7):2011–43, 2015.
- M. Gertler and C. Lown. The information in the high-yield bond spread for the business cycle: evidence and some implications. *Oxford Review of Economic Policy*, 15(3):132–150, 1999.
- M. Gertler, N. Kiyotaki, and A. Prestipino. A macroeconomic model with financial panics. Technical report, National Bureau of Economic Research, 2017.
- M. Gevrey, I. Dimopoulos, and S. Lek. Review and comparison of methods to study the contribution of variables in artificial neural network models. *Ecological Modelling*, 160(3): 249–264, 2003.
- J. Geweke and C. Whiteman. Bayesian Forecasting, in *Handbook of Economic Forecasting*. Elliott, G., Granger, C., and Timmermann, A. (eds.), 2006.
- S. Ghosh and A. Ghosh. Structural vulnerabilities and currency crises. *IMF Staff Papers*, 50 (3):481–506, 2003.
- D. Giannone, M. Lenza, and G. Primiceri. Prior selection for vector autoregressions. *Review of Economics and Statistics*, 97(2):436–451, 2015.
- K. Giesecke, F. Longstaff, S. Schaefer, and I. Strebulaev. Macroeconomic effects of corporate default crisis: A long-term perspective. *Journal of Financial Economics*, 111(2):297–310, 2014.
- S. Gilchrist and J. Leahy. Monetary Policy and Asset Prices. *Journal of Monetary Economics*, 49:75–97, 2002.

- S. Gilchrist and E. Zakrajsek. Credit Spreads and Business Cycle Fluctuations. *American Economic Review*, 102(4):1692–1720, 2012.
- S. Gilchrist, A. Ortiz, and E. Zakrajsek. Credit risk and the macroeconomy: evidence from an estimated DSGE model. *mimeo.*, 2009a.
- S. Gilchrist, V. Yankov, and E. Zakrajšek. Credit market shocks and economic fluctuations: Evidence from corporate bond and stock markets. *Journal of monetary Economics*, 56(4): 471–493, 2009b.
- S. Gonzalez et al. *Neural networks for macroeconomic forecasting: a complementary approach to linear regression models*. Department of Finance Canada, 2000.
- M. Goodfriend and B. McCallum. Banking and interest rates in monetary policy analysis: A quantitative exploration. *Journal of Monetary Economics*, 54(5):1480–1507, 2007.
- C. Goodhart. The future of finance-and the theory that underpins it. *London School of Economics*, 2008.
- C. Goodhart and B. Hofmann. House prices, money, credit, and the macroeconomy. *Oxford Review of Economic Policy*, 24(1):180–205, 2008.
- C. Goodhart and D. Tsomocos. The role of default in macroeconomics. *The Mayekawa lecture, Monetary and Economic Studies, Bank of Japan*, 2011.
- C. Goodhart, B. Hofmann, and M. Segoviano. Bank regulation and macroeconomic fluctuations. *Oxford review of economic Policy*, 20(4):591–615, 2004.
- G. Gopinath, Ş. Kalemli-Özcan, L. Karabarbounis, and C. Villegas-Sanchez. Capital allocation and productivity in South Europe. *The Quarterly Journal of Economics*, 132(4): 1915–1967, 2017.
- G. Gorton and A. Metrick. The run on repo and the panic of 2007-2008. *Unpublished paper, Yale University*, 2009.
- G. Gorton and A. Metrick. Securitized banking and the run on repo. *Journal of Financial economics*, 104(3):425–451, 2012.
- G. Gorton and G. Ordonez. Collateral crises. *American Economic Review*, 104:343–378, 2014.
- G. Gorton and G. Ordonez. Good booms, bad booms. *NBER Working Paper*, w22008, 2016.
- C. Gouriéroux, A. Monfort, and J.-P. Renne. Statistical inference for independent component analysis: Application to structural var models. *Journal of Econometrics*, 196(1):111–126, 2017.
- P.-O. Gourinchas, O. Landerretche, and R. Valdes. *Lending booms: Some stylized facts*. Citeseer, 1999.
- R. Greenwood and D. Scharfstein. The growth of finance. *Journal of Economic Perspectives*, 27(2):3–28, 2013.

- R. Greenwood, S. Hanson, and J. Stein. A comparative-advantage approach to government debt maturity. *The Journal of Finance*, 70(4):1683–1722, 2015.
- M. Guerini, A. Moneta, M. Napoletano, and A. Roventini. The janus-faced nature of debt: Results from a data-driven cointegrated SVAR approach. *LEM Papers Series*, 2017/04, 2017.
- C. Gust and D. Lopez-Salido. Monetary policy and the cyclicity of risk. *Journal of Monetary Economics*, 62:59–75, 2014.
- R. Hall. Why does the economy fall to pieces after a financial crisis? *Journal of Economic Perspectives*, 24(4):3–20, 2010.
- J. Hamilton. A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica: Journal of the Econometric Society*, pages 357–384, 1989.
- J. Hamilton. Time series analysis. *Princeton University Press*, 1994.
- A. Hansen. Economic progress and declining population growth. *The American Economic Review*, 29(1):1–15, 1939.
- L. Hansen and R. Hodrick. Forward exchange rates as optimal predictors of future spot rates: An econometric analysis. *Journal of Political Economy*, 88(5):829–853, 1980.
- D. Harding and A. Pagan. Dissecting the cycle: a methodological investigation. *Journal of Monetary Economics*, 49:365–381, 2002.
- D. Harding and A. Pagan. Synchronization of cycles. *Journal of Econometrics*, 132:59–79, 2006.
- P. Hartmann, K. Hubrich, M. Kremer, and R. Tetlow. Melting down: Systemic financial instability and the macroeconomy. Technical report, Annual Conference 2013 (Duesseldorf): Competition Policy and Regulation in a Global Economic Order 80487, 2015.
- A. Harvey. Trends and cycles in macroeconomic time series. *Journal of Business & Economic Statistics*, 3(3):216–227, 1985.
- A. Harvey. Forecasting, structural time series models and the Kalman filter. *Cambridge University Press*, 1989.
- A. Harvey. Modelling the Phillips curve with unobserved components. *Applied Financial Economics*, 21(1-2):7–17, 2011.
- A. Harvey and A. Jaeger. Detrending, stylized facts and the business cycle. *Journal of applied econometrics*, 8(3):231–247, 1993.
- T. Hastie, R. Tibshirani, and J. Friedman. Unsupervised learning. In *The elements of statistical learning*, pages 485–585. Springer, 2009.
- J. Hatzius, P. Hooper, F. Mishkin, K. Schoenholtz, and M. Watson. Financial conditions indexes: a fresh look after the financial crisis. *NBER Working Papers*, 16150, 2010.

- F. Hayashi. Tobin's marginal q and average q : A neoclassical interpretation. *Econometrica: Journal of the Econometric Society*, pages 213–224, 1982.
- F. Hayek. Monetary theory and the trade cycle. *Clifton, New Jersey: Augustus M Kelly reprint 1966*, 1933.
- J. Heckman. *The incidental parameters problem and the problem of initial conditions in estimating a discrete time-discrete data stochastic process and some Monte Carlo evidence*. University of Chicago Center for Mathematical studies in Business and Economics, 1987.
- T. Helbing, R. Huidrom, M. Kose, and C. Otrok. Do credit shocks matter? A global perspective. *IMF Working Paper*, 10/61, 2010.
- J. Helwege and N. Liang. Initial public offerings in hot and cold markets. *Journal of financial and Quantitative Analysis*, 39(3):541–569, 2004.
- N. Hirakata, N. Sudo, and K. Ueda. Chained Credit Contracts and Financial Accelerators. *IMES Discussion Paper Series*, 2009-E-30, 2009.
- S. Hochreiter and J. Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.
- R. Hodrick and E. Prescott. Postwar US business cycles: an empirical investigation. *Journal of Money, Credit and Banking*, 29(1):1–16, 1997.
- B. Hofmann and B. Bogdanova. Taylor rules and monetary policy: a Global Great Deviation? *BIS Quarterly Review*, pages 37–49, September 2012.
- D. Hollo, M. Kremer, and M. Lo Duca. CISS-a composite indicator of systemic stress in the financial system. *European Central Bank Working Paper Series*, 1426, 2012.
- B. Holmstrom and J. Tirole. Financial intermediation, loanable funds, and the real sector. *The Quarterly Journal of Economics*, 112(3):663–691, 1997.
- B. Holmstrom and J. Tirole. Private and public supply of liquidity. *Journal of political Economy*, 106(1):1–40, 1998.
- B. Holmstrom and J. Tirole. Inside and outside liquidity. *Boston: MIT Press*, 2011.
- K. Hornik, M. Stinchcombe, and H. White. Multilayer feedforward networks are universal approximators. *Neural networks*, 2(5):359–366, 1989.
- N. Hristov, O. Hulsewig, and T. Wollmershauser. Loan supply shocks during the financial crisis: evidence from the euro area from a panel VAR with sign restrictions. *mimeo.*, 2011.
- G. Hubbard. Capital Market Imperfections and Investment. *Journal of Economic Literature*, pages 193–225, 1998.
- K. Hubrich and R. Tetlow. Financial stress and economic dynamics: The transmission of crises. *Journal of Monetary Economics*, 70:100–115, 2015.

- K. Hubrich, A. d’Agostino, M. Cervena, M. Ciccarelli, P. Guarda, M. Haavio, P. Jeanfils, C. Mendicino, E. Ortega, M. Valderrama, et al. Financial shocks and the macroeconomy: heterogeneity and non-linearities. *European Central Bank Occasional Paper Series*, 143, 2013.
- A. Hyvärinen. Fast and robust fixed-point algorithms for independent component analysis. *IEEE transactions on Neural Networks*, 10(3):626–634, 1999.
- A. Hyvärinen and E. Oja. Independent component analysis: algorithms and applications. *Neural networks*, 13(4-5):411–430, 2000.
- A. Hyvärinen, K. Zhang, S. Shimizu, and P. Hoyer. Estimation of a structural vector autoregression model using non-gaussianity. *Journal of Machine Learning Research*, 11(May):1709–1731, 2010.
- M. Iacoviello. House prices and business cycles in Europe: A VAR analysis. *Working Papers in Economics*, page 81, 2002.
- M. Iacoviello. Consumption, house prices, and collateral constraints: a structural econometric analysis. *Journal of Housing Economics*, 13(4):304–320, 2004.
- M. Iacoviello. House Prices, Borrowing Constraints and Monetary Policy in the Business Cycle. *American Economic Review*, 95(3):739–764, 2005.
- M. Iacoviello. Financial business cycles. *Review of Economic Dynamics*, 18(1):140–163, 2015.
- D. Igan and P. Loungani. Global housing cycles. *IMF Working Papers*, 12(217), 2012.
- C.-K. Ing. Multistep prediction in autoregressive processes. *Econometric theory*, 19(2):254–279, 2003.
- V. Ivashina and D. Scharfstein. Bank lending during the financial crisis of 2008. *Journal of Financial economics*, 97(3):319–338, 2010.
- T. Jaditz, L. Riddick, and C. Sayers. Multivariate nonlinear forecasting using financial information to forecast the real sector. *Macroeconomic Dynamics*, 2(3):369–382, 1998.
- U. Jermann and V. Quadrini. Macroeconomic Effects of Financial Shocks. *American Economic Review*, 102(1):238–271, 2012.
- S. Johansen. Determination of cointegration rank in the presence of a linear trend. *Oxford Bulletin of Economics and Statistics*, 54(3):383–397, 1992.
- Ò. Jordà, M. Schularick, and A. Taylor. Financial crises, credit booms, and external imbalances: 140 years of lessons. *IMF Economic Review*, 59(2):340–378, 2011.
- Ò. Jordà, M. Schularick, and A. Taylor. When credit bites back. *Journal of Money, Credit and Banking*, 45(s2):3–28, 2013.
- Ò. Jordà, M. Schularick, and A. Taylor. Leveraged bubbles. *Journal of Monetary Economics*, 76:S1–S20, 2015.

- Ò. Jordà, M. Schularick, and A. Taylor. The great mortgaging: housing finance, crises and business cycles. *Economic Policy*, 31(85):107–152, 2016.
- O. Jorda, M. Schularick, and A. Taylor. Macrofinancial History and the New Business Cycle Facts. *NBER Macroeconomics Annual*, 2017.
- A. Justiniano, G. Primiceri, and A. Tambalotti. Investment Shocks and Business Cycles. *Journal of Monetary Economics*, 57(2):132–145, 2010.
- R. Kadiyala and S. Karlsson. Numerical Methods for Estimation and Inference in Bayesian VAR Models. *Journal of Applied Econometrics*, 12:99–132, 1997.
- D. Kahneman and A. Tversky. Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, 47:263–291, 1979.
- R. Kalman. A new approach to linear filtering and prediction problems. *Journal of Basic Engineering, Transactions ASME, Series D*, 82:35–45, 1960.
- R. Kalman and R. Bucy. New results in linear filtering and prediction theory. *Journal of Basic Engineering, Transactions ASME, Series D*, 83:95–108, 1961.
- G. Kaminsky. Currency and banking crises: the early warnings of distress. *International Monetary Fund*, 178, 1999.
- G. Kaminsky. Currency crises: Are they all the same? *Journal of International Money and Finance*, 25(3):503–527, 2006.
- G. Kaminsky and C. Reinhart. The twin crises: the causes of banking and balance-of-payments problems. *American economic review*, 89(3):473–500, 1999.
- A. Kashyap and J. Stein. Monetary policy and bank lending. In *Monetary policy*, pages 221–261. The University of Chicago Press, 1994.
- J. Kennedy. An analysis of revisions to the industrial production index. *Applied Economics*, 25(2):213–219, 1993.
- J.-M. Keynes. The general theory of employment, investment, and money. *London and New York*, 1936.
- C.-J. Kim and C. Nelson. Has the US economy become more stable? A Bayesian approach based on a Markov-switching model of the business cycle. *Review of Economics and Statistics*, 81(4):608–616, 1999.
- C. Kindleberger. Manias, Panics and Crashes. *Basic Books*, 1978.
- C. Kindleberger. Manias, panics and crashes, revised edition. *New York, Basic*, 1989.
- M. King and S. Wadhvani. Transmission of volatility between stock markets. *The Review of Financial Studies*, 3(1):5–33, 1990.
- R. King and R. Levine. Finance and growth: Schumpeter might be right. *The Quarterly Journal of Economics*, 108(3):717–737, 1993.

- R. King and S. Rebelo. Appendix to “low frequency filtering and real business cycles,”. *Journal of Economic dynamics and Control*, 17:207–231, 1993.
- R. King, C. Plosser, J. Stock, and M. Watson. Stochastic trends and economic fluctuations. *American Economic Review*, 81(4):819–840, 1991.
- N. Kiyotaki and J. Moore. Credit cycles. *Journal of Political Economy*, 105(2):211–248, 1997.
- N. Kocherlakota. Creating business cycles through credit constraints. *Federal Reserve Bank of Minneapolis Quarterly Review*, 24(3):2–10, 2000.
- M. Kolasa and M. Rubaszek. Forecasting using dsge models with financial frictions. *International Journal of Forecasting*, 31(1):1–19, 2015.
- G. Koop, D. Korobilis, et al. Bayesian multivariate time series methods for empirical macroeconomics. *Foundations and Trends® in Econometrics*, 3(4):267–358, 2010.
- S. Koopman, N. Shephard, and J. Doornik. Statistical algorithms for models in state space using SsfPack 2.2. *Econometrics Journal*, 2:113–166, 1999.
- S.-J. Koopman and A. Lucas. Business and default cycles for credit risk. *Journal of Applied Econometrics*, 20(2):311–323, 2005.
- A. Korinek. Thoughts on DSGE Macroeconomics: Matching the Moment, But Missing the Point? *SSRN Electronic Journal*, 2017.
- D. Korobilis. Forecasting in vector autoregressions with many predictors. In *Bayesian Econometrics*, pages 403–431. Emerald Group Publishing Limited, 2008.
- P. Krugman. A model of balance-of-payments crises. *Journal of money, credit and banking*, 11(3):311–325, 1979.
- P. Krugman. Balance sheets, the transfer problem, and financial crises. In *International finance and financial crises*, pages 31–55. Springer, 1999.
- P. Krugman. Crises: the next generation. In *Conference Honoring Assaf Razin, Tel Aviv*, 2001.
- K. Kuttner. Estimating Potential Output as a Latent Variable. *Journal of Business and Economic Statistics*, 12(3):361–368, 1994.
- V. Kuzin, M. Marcellino, and C. Schumacher. Pooling versus model selection for nowcasting gdp with many predictors: Empirical evidence for six industrialized countries. *Journal of Applied Econometrics*, 28(3):392–411, 2013.
- F. Kydland and E. Prescott. Time to build and aggregate fluctuations. *Econometrica: Journal of the Econometric Society*, pages 1345–1370, 1982.
- R. La Porta, F. Lopez-de Silanes, A. Shleifer, and R. Vishny. Legal determinants of external finance. *The Journal of Finance*, 52(3):1131–1150, 1997.

- L. Laeven and F. Valencia. Systemic Banking Crises: A New Database. *IMF working Papers*, 08/224, 2008.
- L. Laeven and F. Valencia. Resolution of banking crises: The good, the bad, and the ugly. *International Monetary Fund*, 10(146), 2010.
- L. Laeven and F. Valencia. Systemic banking crises database: An update. *IMF Working Papers*, 12(163), 2012.
- T. Laubach and J. Williams. Measuring the natural rate of interest. *Review of Economics and Statistics*, 85(4):1063–1070, 2003.
- R. Levine. Finance and growth: theory and evidence. *Handbook of economic growth*, 1: 865–934, 2005.
- E. Levy-Yeyati and U. Panizza. The elusive costs of sovereign defaults. *Journal of Development Economics*, 94(1):95–105, 2011.
- S. Lhuissier. Financial intermediaries’ instability and euro area macroeconomic dynamics. *European Economic Review*, 98:49–72, 2017.
- R. Litterman. A bayesian procedure for forecasting with vector autoregressions and forecasting with bayesian vector autoregressions—four years of experience. *Federal Reserve Bank of Minneapolis*, 1985.
- Z. Liu, P. Wang, and T. Zha. Do credit constraints amplify macroeconomic fluctuations? *Federal Reserve Bank of Atlanta*, 2010-01, 2010.
- M. Lo Duca and T. Peltonen. Assessing systemic risks and predicting systemic events. *Journal of Banking & Finance*, 37(7):2183–2195, 2013.
- F. Longstaff. The subprime mortgage credit crisis and contagion in financial markets. *Journal of Financial Economics*, 97:436–450, 2010.
- G. Lorenzoni. Inefficient credit booms. *The Review of Economic Studies*, 75(3):809–833, 2008.
- G. Lorenzoni. A theory of demand shocks. *American Economic Review*, 99(5):2050–2084, 2009.
- C. Lown and D. Morgan. The credit cycle and the business cycle: new findings using the loan officer opinion survey. *Journal of Money, credit, and Banking*, 38(6):1575–1597, 2006.
- R. Lucas. Econometric policy evaluation: A critique. In *Carnegie-Rochester conference series on public policy*, volume 1, pages 19–46. North-Holland, 1976.
- R. Lucas. Understanding business cycles. *Carnegie-Rochester Conference Series on Public Policy*, 5:7–29, 1977.
- R. Lucas. Methods and problems in business cycle theory. *Journal of Money, Credit and Banking*, 12(4):696–715, 1980.

- H. Lutkepohl. New introduction to multiple time series analysis. *Springer Science & Business Media*, 2005.
- D. Madigan and A. Raftery. Model selection and accounting for model uncertainty in graphical models using Occam’s window. *Journal of the American Statistical Association*, 89(428): 1535–1546, 1994.
- G. Mankiw and M. Shapiro. News or noise? An analysis of GNP revisions, 1986.
- A. Maravall. Unobserved components in economic time series. *European University Institute*, 1993.
- M. Marcellino. Forecast Bias and MSFE encompassing. *Oxford Bulletin of Economics and Statistics*, 62(4):533–542, 2000.
- M. Marcellino and C. Schumacher. Factor MIDAS for nowcasting and forecasting with ragged-edge data: a model comparison for German GDP. *Oxford Bulletin of Economics and Statistics*, 72(4):518–550, 2010.
- M. Marcellino, J. Stock, and M. Watson. Macroeconomic forecasting in the euro area: Country specific versus area-wide information. *European Economic Review*, 47(1):1–18, 2003.
- M. Marcellino, J. Stock, and M. Watson. A Comparison of Direct and Iterated Multistep AR Methods for Forecasting Macroeconomic Time Series. *Journal of Econometrics*, 127(1-2): 499–526, 2006.
- A. Martin and J. Ventura. Economic growth with bubbles. *American Economic Review*, 102(6):3033–58, 2012.
- D. Mayes and M. Virén. Financial conditions indexes. *Economia Internazionale / International Economics*, 55(4):521–550, 2001.
- M. McCracken and S. Ng. FRED-MD: A monthly database for macroeconomic research. *Journal of Business & Economic Statistics*, 34(4):574–589, 2016.
- M. McGowan, D. Andrews, and V. Millot. The walking dead: zombie firms and productivity performance in OECD countries. *OECD Economics Department Working Papers*, 1372, 2017a.
- M. McGowan, D. Andrews, and V. Millot. Confronting the zombies: policies for productivity revival. *OECD Economic Policy Papers*, 21, 2017b.
- R. McKenzie and S. Park. Revisions analysis of the index of industrial production for OECD countries and major non-member economies. Technical report, OECD Short-Term Economic Statistics Working Party meeting, 2006.
- R. Meeks. Do credit market shocks drive output fluctuations? Evidence from corporate spreads and defaults. *Journal of Economic Dynamics and Control*, 36:568–584, 2012.
- C. Meh and K. Moran. The role of bank capital in the propagation of shocks. *Journal of Economic Dynamics and Control*, 34, 2010.

- R. Mehra and E. Prescott. The equity premium: A puzzle. *Journal of monetary Economics*, 15(2):145–161, 1985.
- R. Meinhold and N. Singpurwalla. Understanding the Kalman filter. *The American Statistician*, 37(2):123–127, 1983.
- E. Mendoza and M. Terrones. An anatomy of credit booms: Evidence from macro aggregates and micro data. *NBER Working Paper*, 14049, 2008.
- A. Mian and A. Sufi. The consequences of mortgage credit expansion: Evidence from the us mortgage default crisis. *The Quarterly Journal of Economics*, 124(4):1449–1496, 2009.
- A. Mian and A. Sufi. House prices, home equity-based borrowing, and the us household leverage crisis. *American Economic Review*, 101(5):2132–56, 2011.
- A. Mian, K. Rao, and A. Sufi. Household Balance Sheets, Consumption and the Economic Slump. *Quarterly Journal of Economics*, 128(4):1687–1726, 2013.
- A. Mian, A. Sufi, and E. Verner. Household Debt and Business Cycles Worldwide. *Quarterly Journal of Economics*, 132(4):1755–1817, 2017.
- M. Miller. Debt and taxes. *The Journal of Finance*, 32(2):261–275, 1977.
- H. Minsky. Longer Waves in Financial Relations: Financial factors in more severe depressions. *American Economic Review*, 54(3):324–335, 1964.
- H. Minsky. The Modeling of Financial Instability: An introduction. *Modelling and Simulation*, 5(1):267–272, 1974.
- H. Minsky. Capitalist financial processes and the instability of capitalism. *Journal of Economic Issues*, 14(2):505–523, 1980.
- H. Minsky. Can “it” happen again? Essays on Instability and Finance. *Armonk: M E Sharpe*, 1982.
- H. Minsky. Stabilizing an Unstable Economy. *Yale University Press*, 1986.
- S. Miranda-Agrippino and H. Rey. World asset markets and the global financial cycle. Technical report, National Bureau of Economic Research, 2015.
- F. Modigliani and M. Miller. The Cost of Capital, Corporation Finance and the Theory of Investment. *American Economic Review*, 48:261–297, 1958.
- B. Moll. Productivity losses from financial frictions: Can self-financing undo capital misallocation? *American Economic Review*, 104(10):3186–3221, 2014.
- A. Moneta, D. Entner, P. Hoyer, and A. Coad. Causal inference by independent component analysis: Theory and applications. *Oxford Bulletin of Economics and Statistics*, 75(5):705–730, 2013.

- J. Morley, C. Nelson, and E. Zivot. Why are the Beveridge-Nelson and unobserved-components decompositions of GDP so different? *Review of Economics and Statistics*, 85(2):235–243, 2003.
- A. Musso, S. Neri, and L. Stracca. Housing, consumption and monetary policy: How different are the US and the euro area? *Journal of Banking & Finance*, 35(11):3019–3041, 2011.
- A. Nag and A. Mitra. Neural networks and early warning indicators of currency crisis. *Reserve Bank of India Occasional Papers*, 20(2):183–222, 1999.
- C. Nelson and C. Plosser. Trends and random walks in macroeconomic time series: some evidence and implications. *Journal of monetary economics*, 10(2):139–162, 1982.
- S. Neri et al. *Monetary policy and stock prices: theory and evidence*, volume 513. Banca d’Italia, 2004.
- S. Ng. Boosting recessions. *Canadian Journal of Economics/Revue Canadienne d’Économie*, 47(1):1–34, 2014.
- S. Ng and J. Wright. Facts and challenges from the great recession for forecasting and macroeconomic modeling. *Journal of Economic Literature*, 51(4):1120–54, 2013.
- T. Ng. The predictive content of financial cycle measures for output fluctuations. *BIS Quarterly Review*, pages pp 53–65, June 2011.
- C. Nolan and C. Thoenissen. Financial shocks and the US business cycle. *Journal of Monetary Economics*, 56(4):596–604, 2009.
- M. Obstfeld. Models of currency crises with self-fulfilling features. *European Economic Review*, 40(3-5):1037–1047, 1996.
- A. Okun. Potential GNP: its measurement and significance. *Cowles Commission/Foundation Paper*, 190, 1962.
- J. Olden, M. Joy, and R. Death. An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data. *Ecological Modelling*, 178(3-4):389–397, 2004.
- A. Orphanides and S. Van Norden. The unreliability of output-gap estimates in real time. *Review of economics and statistics*, 84(4):569–583, 2002.
- M. Paustian. Assessing sign restrictions. *The B. E. Journal of Macroeconomics*, 7(1/23), 2007.
- J. Peek and E. Rosengren. The international transmission of financial shocks: The case of Japan. *The American Economic Review*, pages 495–505, 1997.
- J. Peek and E. Rosengren. Unnatural selection: Perverse incentives and the misallocation of credit in Japan. *American Economic Review*, 95(4):1144–1166, 2005.

- G. Peersman. Bank lending shocks and the euro area business cycle. *Working Papers of Faculty of Economics and Business Administration, Ghent University, Belgium*, 2012.
- H. Pesaran, A. Pick, and A. Timmermann. Variable selection, estimation and inference for multi-period forecasting problems. *Journal of Econometrics*, 164(1):173–187, 2011.
- M. Pesaran and R. Smith. Estimating long-run relationships from dynamic heterogeneous panels. *Journal of econometrics*, 68(1):79–113, 1995.
- M. Petersen and R. Rajan. Does distance still matter? The information revolution in small business lending. *The journal of Finance*, 57(6):2533–2570, 2002.
- T. Philippon. The evolution of the US financial industry from 1860 to 2007: Theory and evidence. *NYU Stern Working Paper*, 2008.
- T. Philippon. The bond market’s Q. *The Quarterly Journal of Economics*, 124(3):1011–1056, 2009.
- T. Philippon and A. Reshef. Wages and human capital in the US finance industry: 1909–2006. *The Quarterly Journal of Economics*, 127(4):1551–1609, 2012.
- T. Philippon and A. Reshef. An international look at the growth of modern finance. *Journal of Economic Perspectives*, 27(2):73–96, 2013.
- G. Pinter, K. Theodoridis, and A. Yates. Risk news shocks and the business cycle. *Bank of England working papers*, 483, 2013.
- T. Piskorski, A. Seru, and V. Vig. Securitization and distressed loan renegotiation: Evidence from the subprime mortgage crisis. *Journal of Financial Economics*, 97(3):369–397, 2010.
- Z. Pozsar. Institutional cash pools and the Triffin dilemma of the US banking system. *Financial Markets, Institutions & Instruments*, 22(5):283–318, 2013.
- E. Prieto, S. Eickmeier, and M. Marcellino. Time variation in macro-financial linkages. *Bundesbank discussion paper*, 13, 2013.
- P. Rabanal and M. Taheri Sanjani. Financial Factors: Implications for Output Gaps. *IMF Working Papers*, 15/153, 2015.
- R. Rajan. Has finance made the world riskier? *European Financial Management*, 12(4):499–533, 2006.
- R. Rajan and L. Zingales. Financial Dependence and Growth. *American Economic Review*, 88(3):559–586, 1998.
- R. Rajan and L. Zingales. The great reversals: the politics of financial development in the twentieth century. *Journal of financial economics*, 69(1):5–50, 2003.
- R. Rancière, A. Tornell, and F. Westermann. Decomposing the effects of financial liberalization: Crises vs. growth. *Journal of Banking & Finance*, 30(12):3331–3348, 2006.

- H. Rauch, C. Striebel, and F. Tung. Maximum likelihood estimates of linear dynamic systems. *AIAA journal*, 3(8):1445–1450, 1965.
- C. Reinhart and K. Rogoff. This time is different: Eight centuries of financial folly. *Princeton University Press*, 2009a.
- C. Reinhart and K. Rogoff. The aftermath of financial crises. *American Economic Review*, 99(2):466–72, 2009b.
- C. Reinhart and K. Rogoff. From financial crash to debt crisis. *American Economic Review*, 101(5):1676–1706, 2011.
- C. Reinhart and K. Rogoff. Banking crises: an equal opportunity menace. *Journal of Banking & Finance*, 37(11):4557–4573, 2013.
- C. Reinhart and K. Rogoff. Recovery from financial crises: Evidence from 100 episodes. *American Economic Review*, 104(5):50–55, 2014.
- R. Reis. The Portuguese slump and crash and the euro crisis. Technical report, National Bureau of Economic Research, 2013.
- H. Rey. Dilemma not trilemma: the global financial cycle and monetary policy independence. Technical report, National Bureau of Economic Research, 2015.
- J. Roberto-Ramirez, D. Waggoner, and T. Zha. Structural vector autoregressions: theory or identification and algorithms for inference. *Review of Economic Studies*, 77(2):665–696, 2010.
- J. Robinson. The Generalization of the General Theory, In: The Rate of Interest and Other Essays. *London: MacMillan*, 1952.
- C. Romer and D. Romer. New evidence on the impact of financial crises in advanced countries. *NBER Working Papers*, 21021, 2015.
- C. Romer and D. Romer. Why some times are different: Macroeconomic policy and the aftermath of financial crises. *NBER Working Papers*, 23931, 2017.
- G. Rudebusch. Do Measures of Monetary Policy in a VAR Make Sense? *International Economic Review*, 39(4):907–931, 1998.
- G. Rudebusch and J. Williams. Forecasting recessions: The puzzle of the enduring power of the yield curve. *Journal of Business & Economic Statistics*, 27(4):492–503, 2009.
- D. Rumelhart, G. Hinton, and R. Williams. Learning representations by back-propagating errors. *Nature*, 323(6088):533, 1986.
- G. Rünstler and M. Vlekke. Business, housing, and credit cycles. *Journal of Applied Econometrics*, 33(2):212–226, 2018.
- P. Samuelson. Social indifference curves. *The Quarterly Journal of Economics*, 70(1):1–22, 1956.

- J. Santos. Bank loan pricing following the subprime crisis. *Review of Financial Studies*, 24: 1916–43, 2011.
- F. Schivardi, E. Sette, and G. Tabellini. Credit misallocation during the European financial crisis. *BIS Working Papers*, 669, December 2017.
- M. Schularick and A. Taylor. Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870–2008. *American Economic Review*, 102(2):1029–61, 2012.
- J. Schumpeter. *History of Economic Analysis*. London: Allen and Unwin, 1954.
- R. Shiller. The use of volatility measures in assessing market efficiency. *The Journal of Finance*, 36(2):291–304, 1981.
- R. Shiller. Irrational Exuberance. *Princeton University Press*, 42(3):557–581, 2000.
- S. Shimizu, P. Hoyer, A. Hyvärinen, and A. Kerminen. A linear non-gaussian acyclic model for causal discovery. *Journal of Machine Learning Research*, 7(Oct):2003–2030, 2006.
- H.-S. Shin and K. Shin. Procyclicality and monetary aggregates. *National Bureau of Economic Research*, 2011.
- A. Shleifer and R. Vishny. Unstable banking. *Journal of Financial Economics*, 97(3):306–318, 2010.
- C. Sims. Money, income, and causality. *The American Economic Review*, 62(4):540–552, 1972.
- C. Sims and T. Zha. Bayesian Methods for Dynamic Multivariate Models. *International Economic Review*, 39(4):949–968, 1998.
- C. Sims and T. Zha. Were there regime switches in US monetary policy? *American Economic Review*, 96(1):54–81, 2006.
- C. Sims, T. Zha, et al. Macroeconomic switching. *Manuscript, Princeton University*, 2002.
- F. Smets and R. Wouters. An estimated Dynamic Stochastic General Equilibrium model of the euro area. *Journal of the European Economic Association*, 1(15):1123–1175, 2003.
- F. Smets and R. Wouters. Comparing shocks and frictions in US and euro area business cycles: a Bayesian DSGE approach. *Journal of Applied Econometrics*, 20(2):161–183, 2005.
- F. Smets and R. Wouters. Shocks and frictions in US business cycles: A Bayesian DSGE approach. *American economic review*, 97(3):586–606, 2007.
- A. Smith. *The Theory of Moral Sentiments*. New York: Penguin, 1759.
- A. Smith. *An Inquiry into the Nature and Causes of the Wealth of Nations*. Chicago, Ill: University of Chicago Press, 1776.
- J. Stein. Rational capital budgeting in an irrational world. Technical report, National Bureau of Economic Research, 1996.

- J. Stiglitz. *Freefall: America, free markets, and the sinking of the world economy*. WW Norton & Company, 2010.
- J. Stiglitz. Where modern macroeconomics went wrong. *Oxford Review of Economic Policy*, 34(1-2):70–106, 2018.
- J. Stiglitz and A. Weiss. Credit rationing in markets with imperfect information. *The American Economic Review*, 71(3):393–410, 1981.
- K. Stiroh. Volatility accounting: A production perspective on increased economic stability. *Journal of the European Economic Association*, 7(4):671–696, 2009.
- J. Stock and M. Watson. New indexes of coincident and leading economic indicators. *NBER macroeconomics annual*, 4:351–394, 1989.
- J. Stock and M. Watson. Evidence on structural instability in macroeconomic time series relations. *Journal of Business & Economic Statistics*, 14(1):11–30, 1996.
- J. Stock and M. Watson. Forecasting inflation. *Journal of Monetary Economics*, 44(2):293–335, 1999a.
- J. Stock and M. Watson. Forecasting using principal components from a large number of predictors. *Journal of the American statistical association*, 97(460):1167–1179, 2002a.
- J. Stock and M. Watson. Has the business cycle changed and why? *NBER macroeconomics annual*, 17:159–218, 2002b.
- J. Stock and M. Watson. Forecasting output and inflation: the role of asset prices. *Journal of Economic Literature*, 41(3):788–829, 2003.
- J. Stock and M. Watson. An empirical comparison of methods for forecasting using many predictors. *Manuscript, Princeton University*, 2005.
- J. Stock and M. Watson. Disentangling the channels of the 2007-2009 recession. Technical report, National Bureau of Economic Research, 2012.
- M. Stone. Cross-validatory choice and assessment of statistical predictions. *Journal of the royal statistical society. Series B (Methodological)*, pages 111–147, 1974.
- N. Swanson and H. White. A model selection approach to real-time macroeconomic forecasting using linear models and artificial neural networks. *Review of Economics and Statistics*, 79(4):540–550, 1997.
- A. Swiston. *A US financial conditions index: putting credit where credit is due*, volume 8-161. International Monetary Fund, 2008.
- A. Taylor. The Great Leveraging. *BIS Working Papers*, 398, December 2012.
- J. Taylor. Discretion versus policy rules in practice. In *Carnegie-Rochester conference series on public policy*, volume 39, pages 195–214. Elsevier, 1993.

- J. Taylor et al. Monetary policy and the state of the economy. *Testimony before the Committee on Financial Services, US House of Representatives*, 26, 2008.
- P. Teles and R. Zhou. A stable money demand: Looking for the right monetary aggregate. *J. Payment Sys. L.*, 1:281, 2005.
- P. Temin. Financial Intermediation in the Early Roman Empire. *The Journal of Economic History*, 64(3):705–733, 2003.
- A. Timmermann. Forecast combinations. *Handbook of economic forecasting*, 1:135–196, 2006.
- J. Tobin. A general equilibrium approach to monetary theory. *Journal of money, credit and banking*, 1(1):15–29, 1969.
- J. Tobin and W. Brainard. Financial intermediaries and the effectiveness of monetary controls. *The American Economic Review*, 53(2):383–400, 1963.
- R. Townsend. Optimal contracts and competitive markets with costly state verification. *Journal of Economic theory*, 21(2):265–293, 1979.
- P. Veronesi and L. Zingales. Paulson’s gift. *Journal of Financial Economics*, 97(3):339–368, 2010.
- L. von Mises. The theory of money and credit. *Foundation for Economic Education, New York*, 1912.
- K. Wicksell. The Influence of the Rate of Interest on Prices. *Economic Journal*, 17:213–220, 1907.
- V. Wieland and M. Wolters. The diversity of forecasts from macroeconomic models of the US economy. *Economic Theory*, 47(2-3):247–292, 2011.
- M. Woodford. Interest and prices: Foundations of a theory of monetary policy. *Princeton University Press*, 2003.
- M. Woodford. Financial intermediation and macroeconomic analysis. *Journal of Economic Perspectives*, 24(4):21–44, 2010.
- M. Woodford. Globalization and monetary control. *International Dimensions of Monetary Policy*, J. Gali and M. J. Gertler (eds), 24(4):13–77, 2010b.
- M. Woodford. Inflation targeting and financial stability. *NBER Working Paper*, 17967, 2012a.
- M. Woodford and V. Curdia. Credit frictions and optimal monetary policy. *BIS Working Papers*, 278, 2008.

Résumé

La thèse explore, via différents outils statistiques, les interactions entre la sphère financière et la sphère réelle, dont la compréhension est cruciale pour assurer la stabilité financière. Le chapitre introductif détaille l'importance des frictions financières pour les mécanismes de transmissions macro-financiers, et illustre ces phénomènes avec la récente crise financière. Le deuxième chapitre décompose le Cycle Financier en deux composantes, le Cycle du Crédit et le Cycle des Conditions Financières. Les deux composantes sont identifiées en fonction de leur impact négatif non-linéaire sur l'activité économique et leur pertinence est évaluée à l'aune de leur contribution à la mesure de l'écart de production en temps réel. Le troisième chapitre étudie l'impact réel d'un choc financier structurel, grâce à une méthode d'identification statistique des liens de causalité entre les variables économiques et financières. Le dernier chapitre interroge les fondements de l'instabilité chronique du contenu prédictif des variables financières à l'aide de nombreux modèles économétriques et d'apprentissage automatique.

Mots Clés

liens macro-financiers, frictions financières, Cycle Financier, non-linéarité, chocs financiers, prévision, apprentissage automatique

Abstract

The interplay between financial factors and the real economy is now a focal point of macroeconomic research. The introductory chapter seeks to provide a conceptual framework for the study of macro-financial linkages. The rest of the thesis falls within the impetus to research programs brought to the fore by the recent crisis. The second chapter claims that the Financial Cycle is made up of two different components, the Credit Cycle and the Financial Condition Cycle. The two cycles are identified in the light of their impact on economic activity and their relevance is assessed on the grounds of their contribution for the real-time estimation of the output gap. The third chapter uses a data-driven technique to unravel the contemporaneous causal ordering between economic variables and financial variables and investigates the impact of structural financial shocks on economic activity. The final chapter explores, via a battery of econometric and Machine Learning models, whether the inherently unstable nature of financial variables' predictive power for output is related to the modelling framework or to the variables themselves.

Keywords

macro-financial linkages, financial frictions, financial Cycle, non-linearity, financial shocks, forecasting, machine learning