



# Social interactions, expectation formation and markets

Andreas Karpf

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ECOLE D'ÉCONOMIE DE PARIS - PSE

THÈSE

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présenté par

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## **Social Interactions, Expectation Formation and Markets**

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*Meinen geliebten Eltern*





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## Résumé

Les interactions sociales se trouvent au cœur des activités économiques. Pourtant en sciences économiques, elles ne sont traitées que d'une manière limitée en se concentrant uniquement aux rapports de qu'elles entretiennent avec le marché (Mankiw and Reis, 2002). Le rôle que jouent les interactions sociales vis-à-vis des comportements des agents, ainsi que la formation de leurs attentes sont souvent négligé. Cette négligence reste d'actualité malgré que les premières contributions dans la littérature économique les ont depuis longtemps déjà identifiées comme étant de déterminants importants pour la prise des décisions des agents économiques, comme par exemple Sherif (1936), Hyman (1942), Asch (1951), Jahoda (1959) ou Merton (1968). En revanche, dans les études de consommation (une spécialité au croisement entre les sciences économiques, de la sociologie et de la psychologie), les interactions sociales (influences sociales) sont considérées comme les “... *déterminants dominants [...] du comportement de l'individu...*” (Burnkrant and Cousineau, 1975). Le but de cette thèse est de construire un pont entre les interactions sociales et leur influence sur la formation des anticipations et le comportement des agents.

**Mot-clès:** anticipations, comportement, interactions sociales, réseaux sociaux, ETS, carbone

## Abstract

Social interactions are in the core of economic activities. Their treatment in Economics is however often limited to a focus on the market (Manski, 2000). The role social interactions themselves play for the behavior of agents as well as the formation of their attitudes is often neglected. This is despite the fact that already early contributions in economic literature have identified them as important determinants for the decision making of economic agents as for example Sherif (1936), Hyman (1942), Asch (1951), Jahoda (1959) or Merton (1968). In consumer research, a field on the intersection between Economics, Sociology and Psychology, on the other hand social interactions (social influences) are considered to be the “... *most pervasive determinants [...] of individual's behaviour...*” (Burnkrant and Cousineau, 1975). The thesis at hand bridges the gap between social interactions and their influence on agents expectation formation and behavior.

**Keywords:** expectations, behavior, social interactions, social networks, ETS, carbon





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# Chapter 1

## Introduction

### 1.1 Introduction Française

Les interactions sociales se trouvent au cœur des activités économiques. Pourtant en sciences économiques, elles ne sont traitées que d'une manière limitée en se concentrant uniquement aux rapports de qu'elles entretient avec le marché (Mankiw and Reis, 2002). Le rôle que jouent les interactions sociales vis-à-vis des comportements des agents, ainsi que la formation de leurs attentes sont souvent négligé. Cette négligence reste d'actualité malgré que les premières contributions dans la littérature économique les ont depuis longtemps déjà identifiées comme étant de déterminants importants pour la prise des décisions des agents économiques, comme par exemple Sherif (1936), Hyman (1942), Asch (1951), Jahoda (1959) ou Merton (1968). En revanche, dans les études de consommation (une spécialité au croisement entre les sciences économiques, de la sociologie et de la psychologie), les interactions sociales (influences sociales) sont considérées comme les “... *déterminants dominants [...] du comportement de l'individu...*” (Burnkrant and Cousineau, 1975). Le but de cette thèse est de construire un pont entre les interactions sociales et leur influence sur la formation des anticipations et le comportement des agents. Cette thèse est structuré de la façon suivante:

Les chapitres 2 à 5 de cette thèse abordent la question de la formation des anticipations. Comment les agents forment-ils leurs anticipations, dans quelle mesure sont-ils influencés par les autres agents et quels autres facteurs jouent un rôle dans la création d'un biais potentiel dans les anticipations des agents. De plus je presente une méthodologie indiquant comment les données sur les opinions peuvent être collectées dans l'avenir en utilisant les techniques modernes d'analyse de texte. Dans le chapitre 6 le marché européen des émissions est analysé du point de vue du réseau social. L'objet de l'étude est de déterminer comment la structure du réseau reflète le fonctionnement du marché d'émission et comment la position des agents à l'intérieur du réseau influe sur leur aptitude à créer des revenus en provenance de ces transactions.

L'objet de l'étude des chapitres 2 à 4 de cette thèse concerne la question de la rationalité anticipative. Les premières contributions de Knight (1921) et Keynes (1936) suggèrent déjà que la prise des décisions des agents est largement influencée non seule-



ment par leurs anticipations mais aussi par leur évaluation des risques, reflétant ainsi les aspects psychologiques des agents (Carnazza and Parigi, 2002). Que les agents anticipent rationnellement ou non les changements économiques et les décisions politiques futures, est une question principale à partir de laquelle s'articule une multitude de travaux théoriques en économie. La courbe de Phillips est probablement l'exemple le plus frappant dans ce contexte (Phillips, 1958). Le constat empirique fait par William Phillips affirme que la relation négative qui existe entre le taux d'inflation et le taux de chômage. Ceci a été utilisée ultérieurement comme un levier pour influencer le marché du travail à travers la politique monétaire. Avec Milton Friedman (1968), Sargent et al. (1973) et Lucas (1976), de telles tentatives seraient pourtant, du moins à moyen terme, neutralisées par les agents rationnels qui prennent en compte un taux d'inflation anticipé plus élevé lors de la négociation de leurs salaires. Ainsi, ce n'est pas très surprenant que les hypothèses concernant les anticipations d'inflation, mais également d'autres variables économiques, soient cruciales aussi bien pour la théorie économique que pour la prise de décision politique.

Étant donné l'importance des anticipations dans la théorie économique, les premiers défenseurs de l'économie comportementale tels que George Katona se sont dévoués au développement des instruments qui permettent de mesurer les attitudes et les anticipations des agents économiques vis-à-vis de l'économie. Le travail réalisé dans la première période de l'après-guerre par Katona est à l'origine de la recherche économique fondée sur des sondages et a conduit à la création des indicateurs de confiance des consommateurs et des entreprises. Ceci représente encore aujourd'hui une source importante de données en complément des variables macroéconomiques quantifiables des tendances de prévision et d'évaluation de l'économie (Katona, 1974). L'indice de confiance des consommateurs de l'Université du Michigan (MCSI), conceptualisé par George Katona et régulièrement mis à jour depuis 1955, ainsi que l'indice de confiance des consommateurs (CCI), qui a été lancé en 1967 et qui est actuellement entretenu par le Conference Board des États-Unis, sont des exemples anciens et reconnus d'indices adressées aux ménages. Les données transversales provenant du premier de ces deux indices sont utilisées dans les chapitres 3 et 4. Un autre exemple de ce genre des données est l'Enquête mensuelle de conjoncture auprès des ménages français (ECAMME), dont les données microéconomiques sont utilisées au Chapitre 2. L'évaluation des avis économiques fondée sur les sondages a été étendue plus tard aux entreprises. L'indice de la Fed de Philadelphie, effectué depuis 1968, ou l'indice allemand IFO du climat des affaires crée à la fin des années 1940 et régulièrement publié depuis 1972, peuvent être cités à titre d'exemple dans ce contexte. Des données similaires sont actuellement collectées dans toutes économies des pays développés. En outre, il existe aussi des indicateurs composites, comme par exemple l'Indicateur européen du climat économique (ESI) établi par la Commission européenne et qui combine de données en provenance des ménages et des entreprises pour des pays et des industries différents. D'autres sondages sur la confiance visent un public hautement spécialisé, comme par exemple les prévisionnistes professionnels ou les responsables d'achats. Un exemple de la première catégorie serait le Philadelphia Fed's Survey of Professional Forecasters.



Les données sur les anticipations des agents typiquement collectées dans les enquêtes de consommation sont qualitatives et non quantitatives. Cela signifie, en ce qui concerne par exemple l'évolution de l'inflation, que l'on demande aux répondants de choisir entre différentes catégories ordonnées au lieu de donner un chiffre précis de celui-ci pour un laps de temps donné (par exemple les prochains douze mois). Comme nous verrons plus tard, les individus ont un bon flair en ce qui concerne la tendance, mais manquent souvent d'une notion exacte de la grandeur. Si, comme dans la plupart des cas, seulement l'information qualitative sur les anticipations est disponible, de méthodes différentes de quantification peuvent être utilisées. On peut alors regrouper ces approches en deux catégories: D'une part l'approche régressive, dont l'origine peut être retracée jusqu'à Anderson (1952), Pesaran (1985, 1987) mais aussi bien qu'à Pesaran and Weale (2006a). D'autre part l'approche probabiliste qui a été initialement développée par Theil (1952) et Carlson and Parkin (1975) et qui est ainsi souvent désignée par ce dernier comme "*l'approche de Carlson-Parkin*". Les éléments discutés ci-dessus seront repris dans différents chapitres de la thèse. Il s'ensuit une discussion en détail des chapitres respectifs.

Le **chapitre 2** cherche à savoir si la formation des anticipations individuelles d'inflation est biaisée dans le sens du consensus et est ainsi contrainte au comportement grégaire. En s'appuyant sur l'approche traditionnelle de Carlson-Parkin pour quantifier les données qualitatives des sondages et sur l'extension de celui-ci réalisé par Kaiser and Spitz (2002) dans un cadre sondé ordonné, je propose une méthode qui permet d'obtenir des anticipations individuelles du niveau d'inflation en utilisant une évaluation hiérarchique bayésienne de Monte Carlo d'une chaîne de Markov (MCMC). Cette méthode est appliquée aux données microéconomiques sur les anticipations des ménages à partir de l'"Enquête mensuelle de conjoncture auprès des ménages – ECAMME" (de janvier 2004 à décembre 2012). Puisque l'ensemble de données de l'ECAMME ne contient qu'une structure de panel très basique, une fraction des ménages est interviewée pendant trois mois consécutifs. L'algorithme de carte auto-organisatrice de Kohonen (Kohonen, 1982) est utilisé pour créer un pseudo panel afin d'être en mesure de retracer les perceptions et les anticipations des différentes cohortes sur toute la période disponible des données. Finalement une version modifiée du test non-paramétrique développé originalement par Bernardt et al. (2006) pour expliquer le comportement grégaire est réalisée. La modification permet d'appliquer le test directement aux distributions ultérieures au niveau des cohortes résultant de la méthode d'évaluation du MCMC. Je démontre que la formation des anticipations n'est pas biaisée dans le sens du consensus. Au contraire, elle expose une forte tendance anti-grégaire, ce qui est conforme aux résultats d'autres études (Rülke and Tillmann, 2011) et soutient la notion des anticipations hétérogènes.

Le **chapitre 3** étudie les raisons possibles de la distorsion des anticipations des agents. Contrairement au chapitre précédant, les données du Michigan Consumer Survey sont utilisées ici, puisqu'elles contiennent une structure de panel basique. Cela signifie qu'un pourcentage élevé de répondants peut être retrouvé dans l'ensemble d'interviewés douze mois après leur première interview. Afin de classer les répondants entre agents "rationnels" et "non-rationnels", j'utilise la structure de panel du Michigan Consumer Survey, ainsi que ses questions sur les anticipations et les perceptions des agents douze mois



plus tard concernant les différentes variables économiques. Dans le cas d'indisponibilité des variables de perception, j'utilise une technique de quantification d'information qualitative des sondages qui se sert du Hierarchical Ordered Probit pour les construire (Lahiri and Zhao, 2015). Ensuite, l'écart entre les individus rationnels et non-rationnels est décomposé en utilisant la technique détaillée d'Oaxaca-Blinder linéaire (Oaxaca, 1973; Blinder, 1973; Yun, 2004) et non-linéaire (Bauer and Sinning, 2008). Les moments des estimations sont calculés selon les méthodes exposées par Rao (2009) et Powers et al. (2011). Les codes, utilisés dans ce chapitre pour le modèle HOPIT, ainsi que pour la méthode de décomposition, ont dû être écrits à partir de zéro. Les codes R et C++ peuvent être retrouvés respectivement dans les annexes B et C du même chapitre.

Je demontre que le biais rationnel peut être expliqué, dans une grande mesure, par les variables sociodémographiques contenues dans le Michigan Consumer Survey (éducation, âge, etc.) et par d'autres variables observables. On retrouve ces variables dans le sondage lui-même, comme par exemple la consommation d'information du répondant avant l'interview, ce qui se révèle être un déterminant significatif pour le biais "rationnel" faisant l'objet de l'enquête. Il en résulte que, le biais anticipatif n'est probablement pas une question de rationalité, mais il reflète plutôt les expériences et les perceptions des individus sur la situation économique dans la vie quotidienne. Ce constat peut être considéré en lien avec les résultats du chapitre 2.

Le **chapitre 4** se focalise sur le rôle qui a l'influence sociale dans la formation des anticipations des agents économiques. Tout comme dans le chapitre 3, l'ensemble des données transversales répétées du Michigan Consumer Survey est transformé en un pseudo-panel en utilisant les cartes auto-organisatrices de Kohonen (Kohonen, 1982). Ceci permet de surveiller la formation des anticipations des cohortes sur toute la période disponible (janvier 1978 à juin 2013). Ensuite, le concept théorique d'information "*transfer entropy*" (Schreiber, 2000) est utilisé pour révéler le rôle des influences sociales dans la formation des anticipations, ainsi que pour souligner la structure de réseau. Finalement la correction de Panzeri-Treves (Panzeri and Treves, 1996) est appliquée au début de la procédure d'évaluation, afin de contrôler pour un possible biais d'échantillonnage. Je demontre que l'influence sociale dépend fortement des caractéristiques sociodémographiques et coïncide aussi avec un haut degré de connectivité et une position centrale à l'intérieur du réseau d'influence sociale. Le réseau d'influence sociale construit de cette manière suit la loi de puissance et expose ainsi une structure similaire aux réseaux observés dans d'autres contextes.

Le **chapitre 5** présente une méthodologie conseillé pour la collecte de données d'opinion pour son implémentation dans le futur. Comme il a été discuté plus haut, jusqu'à présent, ce processus de collecte de données dépendait fortement des sondages pour évaluer les opinions et les anticipations des agents économiques concernant les prospections économiques ou les perceptions des évolutions économiques antérieures. Dans l'hypothèse que l'Internet sert aujourd'hui de large réservoir pour l'expression d'opinions et d'anticipations, ce chapitre propose une méthodologie pour construire un indicateur d'opinions économiques qui analyse des données textuelles non-structurées disponibles librement sur l'internet. Ceci est possible en utilisant des technologies



modernes d'analyse d'opinion et de texte en combinaison avec l'analyse économétrique traditionnelle. Le site web [www.insen.eu](http://www.insen.eu) fondée sur le principe de “*crowdsourcing*” est présenté dans ce chapitre. Ce dernière été mis en place en vue de ce projet afin de collecter un ensemble de données d'apprentissage nécessaires à la construction de l'indicateur d'opinions économiques web. Un indicateur d'opinion fondé sur le web selon la méthodologie décrite est capable de fournir plus d'information actualisée sur les opinions des individus que le sondage mensuel traditionnel, ce qui permet d'identifier les tendances économiques aussitôt qu'elles apparaissent.

Dans le **chapitre 6**, la notion d'interactions sociales est contextualisée. Le système européen d'échange de quotas d'émission (ETS) est analysé de point de vu du réseau. Le système européen d'échange de quotas d'émission a été créé en 2005 afin de remplir les objectifs de réduction d'émissions, conformément à ce qui a été défini par le Protocol de Kyoto et au plus bas coût. L'échange des quotas d'émissions cherche à exploiter les différents coûts marginaux entre pays, entreprises, industries ou même différentes branches à l'intérieur d'une compagnie. Le cout marginal engendrée par la réduction d'une unité supplémentaire d'émissions de gaz à effet de serre. Le système est fondé sur un principe de “plafonnement”, selon lequel les unités d'émission autorisées, appelés des quotas d'émission, sont allouées aux émetteurs de gaz à effet de serre. Ces quotas sont attribués en tenant en compte des données historiques d'émissions. Ils sont plafonnés en fonction des objectifs fixés de réduction des émissions. Ainsi, les quotas d'émissions deviennent un bien rare que les participants peuvent échanger ou négocier sur le marché. Les participants au marché qui sont légalement obligés de réduire leurs émissions doivent périodiquement céder le montant de quotas d'émission se trouvant en leur possession. Ceux-ci sont ensuite comparés avec les émissions effectuées, qui sont enregistrées en permanence par les installations correspondantes dans le but de vérifier si les objectifs de réduction des émissions ont été atteints. Si les quotas disponibles ne satisfont pas les émissions réalisées, le participant se voit dans l'obligation de payer une amende proportionnelle aux quotas d'émissions qui lui ont fait manquer les obligations ciblés de réduction des émissions. Les installations concernés peuvent être des usines, des centrales électriques ou même des avions. Actuellement, il y a autour de 11.000 installations qui sont intégrées dans l'ETS. L'ETS n'est pas seulement ouvert aux entreprises devant se conformer aux objectifs de réduction des émissions de gaz à effet de serre. D'autres entités, n'ayant pas d'obligation réglementaire, sont admises aussi, contre paiement, à négocier sur le marché d'émissions. Les quotas d'émission peuvent être négociés bilatéralement, en vente libre via un courtier ou sur un des marchés européens d'échanges climatiques (marché au comptant). Pour la période, pour laquelle l'ensemble de données de transactions est disponible (2005–2011), la forme la plus commune de transactions était “la vente libre”.

C'est une obligation légale pour chaque transaction dans l'ETS d'être enregistrée dans un système comptable. Cette information est accessible au public avec un délai de trois ans. Au début, ces registres étaient organisés au niveau national. Depuis 2008, cette fonction est assurée par le Journal des Transactions Communautaire Indépendant (CITL) accessible en ligne sur <http://ec.europa.eu/environment/ets/>. Les don-



nées des transactions provenant du CITL constituent la base de l'analyse fondée sur les réseaux de l'ETS de l'UE réalisée dans le chapitre 6. L'ensemble de données sur les transactions proviennent du CITL. Elles contiennent le cachet de l'heure exacte de la transaction, son volume, l'information sur les comptes actifs, ainsi que les données sur l'attribution des quotas, la cession des quotas et les émissions vérifiées. L'ensemble de données brutes contient approximativement 520.000 transactions, auxquelles ont été ajoutées les informations sur les prix comptant d'après Bloomberg, ainsi que les données sur la structure de propriété et le type d'entreprise (Jaraite et al., 2013).

Une analyse fondée sur le réseau du marché européen des quotas d'émission est alors réalisée. Nous construisons un réseau fondé sur l'ensemble de données transactionnelles. Les agents actifs sur le marché des quotas d'émission sont considérés comme des sommets. Ces sommets sont reliés par des arêtes dirigées sous forme de transactions depuis le vendeur (le sommet source) jusqu'à l'acheteur (le sommet cible). Les arêtes sont pondérées par le volume d'EUA transférés au cours de la transaction respective. Le but est d'examiner le lien qui existe entre la structure du réseau et le fonctionnement du marché. Par ailleurs, nous étudions si l'organisation du marché se voit reflétée dans la structure du réseau: Quels facteurs sont pertinents pour le processus de concordance au sein du ETS? Est-ce que la structure du réseau soutient l'idée d'exploitation par le marché de quotas d'émissions de la différence dans les coûts de réduction marginaux? Est-ce que la position d'un agent à l'intérieur du réseau a une implication sur son aptitude à créer des revenus à partir de la négociation? Nous démontrons que le réseau présente une forte structure centre-périphérie, aussi reflétée dans le processus de formation du réseau : En raison d'un manque de places du marché centralisé, les opérateurs des installations sujettes aux règlements du ETS de l'UE doivent recourir aux réseaux locaux d'intermédiaires financiers s'ils souhaitent participer au marché. Il est démontré que cela compromet l'idée centrale du ETS, à savoir celle d'exploiter les différents coûts de réduction marginaux.

## 1.2 English Introduction

Social interactions are in the core of economic activities. Their treatment in Economics is however often limited to a focus on the market (Manski, 2000). The role social interactions themselves play for the behavior of agents as well as the formation of their attitudes is often neglected. This is despite the fact that already early contributions in economic literature have identified them as important determinants for the decision making of economic agents as for example Sherif (1936), Hyman (1942), Asch (1951), Jahoda (1959) or Merton (1968). In consumer research, a field on the intersection between Economics, Sociology and Psychology, on the other hand social interactions (social influences) are considered to be the “... *most pervasive determinants [...] of individual's behaviour...*” (Burnkrant and Cousineau, 1975). The thesis at hand bridges the gap between social interactions and their influence on agents expectation formation and behavior.

In Chapters 2 to 5 of this thesis the question of expectation formation is addressed.



How do agents form their expectations, how are they influenced by other agents in this process and which other factors could play a role for an expectational bias? Moreover a concept is presented how sentiment data could be collected in the future using modern text mining techniques. In Chapter 6 of the thesis the European emission market is analyzed from a social network perspective. It is investigated how the network structure reflects the functioning of the market and how the position of agents within the network influences their ability to create revenues from trading.

In Chapters 2 to 4 of this thesis the question of expectational rationality is investigated. Already early contributions of Knight (1921) and Keynes (1936) suggest that decision making of economic agents is largely influenced by their expectations and their assessment of risk, reflecting not least psychological aspects (Carnazza and Parigi, 2002). Whether agents rationally anticipate future economic developments or policy decisions or not, is thus a question on which a multitude of theoretical economic work hinges. The Phillips curve is in this context probably the most prominent example (Phillips, 1958). The empirical finding by William Phillips asserts a negative relationship between the inflation rate and the unemployment rate, which subsequently was used as a mechanic to influence the labor market via monetary policy. Along Milton Friedman (1968), Thomas Sargent et al. (1973) and Robert Lucas (1976) such attempts would however at least in the medium run be neutralized by rational agents, who take an anticipated higher future inflation rate into account when negotiating their wages. It is thus not very surprising that assumptions about expectations with regard to the inflation but also other economic variables are crucial for economic theory as well as for policy making.

Given the importance of expectations for economic theory, early proponents of behavioral economics such as George Katona devoted themselves to develop instruments to measure attitudes and expectation of economic agents towards the economy. Katona's work eventually resulted in the field of survey based economic research and led to the creation of survey based consumer and business confidence indicators in the early post-war period, which until today represent important sources of data complementary to measurable macroeconomic variables in forecasting and evaluating trends in the evolution of the economy (Katona, 1974). The University of Michigan Consumer Sentiment Index (MCSI), conceptualized by George Katona and regularly updated since 1955, or the Consumer Confidence Index (CCI), which started in 1967 and is since then updated and maintained by the U.S. Conference Board are early and well known examples of indicators directed at households. Cross section data from the former of these two indicators is used in Chapter 3 and Chapter 4. Another example of a household survey is the French *Enquête mensuelle de conjoncture auprès des ménages* (ECAMME) of which micro-level data was used in **Chapter 2**. The survey based assessment of economic sentiment was later on extended to businesses. The Philadelphia Fed Index, conducted since 1968, or the German IFO Business Climate index, which originated in the late 1940s and is regularly published since 1972, can be cited exemplarily in this context. Similar data is nowadays collected in each major economy. Additional to that, so called composite indicators can be found, as for example the European Economic Sentiment Indicator (ESI) compiled by the European Commission, which combines data from households



and businesses in different countries and industries respectively. Other sentiment surveys are addressed to highly specialized audiences as for example professional forecasters or purchasing managers. An example for the former category would be the Philadelphia Fed's Survey of Professional Forecasters.

The data about agents expectations typically collected in consumer or household surveys is qualitative and not quantitative. This means, with regard to for example the evolution of inflation, respondents are normally asked to choose between different ordered categories instead of giving a precise number of the expected inflation rate in for instance twelve months from the time of the interview. As will be seen later on, individuals have a good feeling for the trend but often lack an accurate notion of the magnitude. To control for the problem that only qualitative expectation information is available in most of the cases, different quantification methods can be used. The approaches therefore can be grouped into two categories: the *regression approach* which roots can be tracked back to Anderson (1952), Pesaran (1985, 1987) as well as Pesaran and Weale (2006b) on the one hand, and the *probability approach* which was initially developed by Theil (1952) and Carlson and Parkin (1975) respectively, and thus is often denominated by the latter as the *Carlson-Parkin approach* on the other hand. The different chapters in this thesis make use of the elements discussed above. In detail the following topics are discussed in the respective chapters.

**Chapter 2** investigates whether the formation of individual inflation expectations is biased towards a consensus and is thus subject to herding behavior. Basing on the traditional Carlson-Parkin approach to quantify qualitative survey expectations and its extension by Kaiser and Spitz (2002) in an ordered probit framework, a method to gain individual level inflation expectations is proposed using a Markov chain Monte Carlo Hierarchical Bayesian estimation method. This method is applied to micro survey data on inflation expectations of households from the monthly French household survey "Enquête mensuelle de conjoncture auprès des ménages - ECAMME" (January 2004 to December 2012). Since the ECAMME dataset only contains a very basic panel structure, a fraction of households is interviewed three months in a row, the self-organizing Kohonen map algorithm (Kohonen, 1982) is used to create a pseudo panel in order to be able to track inflation perceptions/expectations of different cohorts over the whole time period in which the dataset is available. Finally, a modified version of the non-parametric test for herding behavior by Bernardt et al. (2006) is conducted. The modification is such that the test can directly be applied to cohort-level posterior distributions resulting from the MCMC estimation method. It is shown that the expectation formation is not subject to a bias towards the consensus. In contrast, it exhibits a strong anti-herding tendency which is consistent with the findings of other studies (Rülke and Tillmann, 2011) and supports the notion of heterogeneous expectations.

**Chapter 3** studies possible reasons for the rationality bias in agents expectations. In contrast to the previous chapter, here data from the Michigan Consumer Survey is used since it contains some sort of basic panel structure. This means that a high percentage of respondents can be found again in the pool of interviewees twelve months after their first interview. This panel structure of the Michigan Consumer Survey together with its



survey questions about expectations with regard to different economic variables as well as perceptions thereof twelve months later is used to group respondents into “rational” and “non-rational” agents. If the perception variables were not available, a technique to quantify qualitative survey information using an Hierarchical Ordered Probit model (Lahiri and Zhao, 2015) is used to construct them. Then the expectational gap between rational and non-rational individuals is decomposed using a detailed linear (Oaxaca, 1973; Blinder, 1973; Yun, 2004) / non-linear (Bauer and Sinning, 2008) Oaxaca-Blinder decomposition. The moments of the estimates are computed along the methods outlined by Rao (2009) and Powers et al. (2011). The code for both the HOPIT model as well as the decomposition method used in this chapter had to be written from scratch. The R and C++ code can be found in Appendices B and C of the same chapter respectively.

It is shown that the rationality bias can be to a large and significant degree explained by sociodemographic variables contained in the Michigan Consumer Survey (education, age, etc.) and other observable variables. The latter group comprises variables stemming from the survey questions themselves, as for example the consumption of news by the respondents prior to the interview which turns out to be a significant determinant for the “rationality”-bias under investigation. The expectational bias is thus probably not so much a question of rationality but more reflects the experiences and perceptions of individuals of the economy in daily live. This outcome can be seen in line with the results from Chapter 2.

**Chapter 4** investigates the role of social influence for the expectation formation of economic agents. Like in Chapter 3 the repeated cross-section data set of the University of Michigan consumer survey is transformed into a pseudo-panel using self-organizing Kohonen maps (Kohonen, 1982). This allows to monitor the expectation formation of cohorts over the whole available time span (January 1978 to June 2013). Subsequently the information theoretic concept of transfer entropy (Schreiber, 2000) is used to reveal the role of social influences on the expectation formation as well as the underlying network structure. To control for a possible sampling bias the Panzeri-Treves correction (Panzeri and Treves, 1996) is eventually applied on top of this estimation procedure. It is shown that social influence strongly depends on sociodemographic characteristics and also coincides with a high degree of connectivity and a central positions within the network of social influence. The network of social influence inferred in this way follows a power-law and thus exhibits a similar structure as networks observed in other contexts.

**Chapter 5** lays out a concept how economic sentiment data could be collected in the future. As discussed above, this data collection process up to now heavily relies on surveys to evaluate opinions and expectations of economic agents regarding economic prospects or perceptions of past economic evolutions. Under the assumption that the internet nowadays serves as a large reservoir for the expression of opinions and expectations, this chapter proposes a concept to construct an economic sentiment indicator analyzing unstructured textual data which is freely available on the internet making use of modern text and sentiment mining technologies in combination with traditional econometric analysis. The crowd-sourcing website [www.insen.eu](http://www.insen.eu) is presented. It was set up for this project in order to collect a training dataset for the envisioned web-based eco-



conomic sentiment indicator. It is argued that a web-based sentiment indicator, along the concept outlined, will be able to deliver more up-to-date sentiment information than the traditional monthly survey based sentiment indicators, which allows to track economic trends as they are emerging.

In **Chapter 6** the notion of social interactions is brought into a market context. The European Emission Trading System (ETS) is analyzed from a network perspective. The European Emission trading System was created in 2005 in order to fulfill the targets for the reduction of green house gas emissions into the atmosphere along what was defined by the Kyoto Protocol as cost efficient as possible. Emission Trading seeks to exploit differing marginal abatement costs, this is the marginal cost of reducing green house gas emission by one unit, between countries, firms, industries or even between different branches within a company. The system bases on a “*cap-and-trade*” principle in which permitted emission units, so called allowance units are allocated to emitters of green house gases. These assigned allowance units normally depend on historical yearly green house gas emission data and are capped with regard to committed emission reduction targets. Thereby allowance units become a scarce good which participants can exchange/trade in a market. Periodically market participants who are legally committed to reduce their emissions have to surrender the amount of allowance units in their possession. These are subsequently compared with the realized emissions which are permanently recorded at the respective installations, to check if the emission reduction targets were met. If the available allowance units fall short of the realized emissions, the obliged market participant has to pay a fine proportional to the allowance units by which the emission reduction obligations were missed. Installations can be factories, power plants or even aircrafts. Currently there are around 11,000 installations captured by the ETS. The ETS is open not only to companies who have to comply with greenhouse gas emission reduction targets. Also other entities which don’t fall under the ETS regulation are against a fee allowed to trade on the emission market. Allowance units can be traded bilaterally, over the counter via a broker or on one of Europe’s climate exchange markets (spot markets). For the time for which the transaction data set is available (2005 - 2011) the most common form of transactions was “over the counter”.

It is a legal obligation that each transaction in the ETS is recorded in some sort of accounting system (registries). This data is accessible to the public with an embargo of three years. At the beginning these registries were organized on a national level. Since 2008 this function is resumed by a central Community Independent Transaction Log (CITL) accessible online under <http://ec.europa.eu/environment/ets/>. The transaction data from the CITL form the base of the network-based analysis of the EU ETS conducted in Chapter 6. The transaction data set was scraped from the CITL. It contains the exact time stamp of the transaction, its volume, information about the accounts active in the ETS as well as data with regard to the allowance allocation, the surrendering of the allowances as well as the verified emissions. The raw data set contains approximately 520,000 transactions to which spot price information from Bloomberg as well as data about the ownership structure and the type of the respective companies (Jaraite et al., 2013) were added.



A network based analysis of the European Emission market is then performed. Therefore a network based on the transaction data set is constructed. Agents active in the emission market are thereby regarded as vertices. These vertices are connected by directed edges in the form of transactions from the seller (the source vertex) to the buyer (the target vertex). The edges are weighted by the volume of EUAs transferred in the respective transaction. The aim is to investigate the connection between the network structure and the functioning of the market. Among other things it is studied whether the organization of the market is reflected in the network structure, which factors are relevant for the matching process in the ETS, whether the network structure is supporting the idea of emission markets to exploit differences in marginal abatement costs and whether the position of an agent within the network has an implication for its ability to create revenues out of a trade. It is shown that the network exhibits a strong core-periphery structure also reflected in the network formation process: Due to a lack of centralized market places, operators of installations which fall under the EU ETS regulations have to resort to local networks or financial intermediaries if they want to participate in the market. It is argued that this undermines the central idea of the ETS, namely to exploit marginal abatement costs.





## Chapter 2

# Herd behavior in consumer inflation expectations - Evidence from the French household survey<sup>1</sup>

### 2.1 Introduction

Assumptions about expectations regarding inflation are exceedingly relevant for economic theory as well as policy making. Consumer surveys measuring households' perceptions and expectations regarding the evolution of prices thus have developed into important supplementary tools for monetary authorities and a vivid field of research. The latter is foremost motivated, besides the fact that inflation is an important economic variable directly impacting the welfare of households, by the discussion if and to what degree inflation is fully anticipated and thus if expectations are rational or unbiased. The falsification or verification of several economic theories as for example the well known Phillips curve (Phillips, 1958), heavily base on this question.

**Rational Expectations - a short history** The theoretical foundation for the notion of rational expectations was laid by the seminal work of Muth (1961). Along Muth agents form their expectations with regard to the future evolution of an economic variable by taking into account to their best knowledge all relevant information available. Under Muth's strong version of expectational rationality this implies that the expectations of an agent are equivalent to the mathematical notion of conditional expectations. As far as expectations in period  $t$  with regard to inflation in period  $t + 1$  are concerned (as relevant in the context of this study), this implies (Snowdon and Vane, 2005, pp. 225):

$$P_{t+1}^e = E(P_t | \Omega_{t_1})$$

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<sup>1</sup>This chapter bases on a working paper published in the working paper series of the Economics Faculty of the University Paris 1 Panthéon-Sorbonne (Karpf, 2013).



Here  $P_t$  corresponds to the actual inflation rate at time  $t$  and  $\Omega_{t-1}$  to the inflation set available to the individual in time  $t - 1$ . Muth thus implicitly assumes that agents choose a prediction model which along their knowledge is the most accurate. Forecast errors, Muthian expectational rationality doesn't correspond to perfect foresight, are due to incomplete information. Muth also assumes that the expectation formation of agents is not subject to systematic errors. Along Muth a learning effect would lead agents to readjust their prediction model once they realize that their intrinsic forecasting method is erroneous. Sticking to the example of inflation expectations this implies that rational expectations following Muth exhibit a serially uncorrelated random error  $\epsilon_t$  with mean zero which is independent from the available information set (Snowdon and Vane, 2005, pp. 225):

$$P_{t+1}^e = P_t + \epsilon_t$$

The assumption that the error term is uncorrelated from the information set is necessary since this would otherwise imply that agents don't take full advantage of the information available to them.

The rational expectation hypothesis largely replaced the adaptive expectation hypothesis which was dominant in economic modelling up to the 1970ies. In the adaptive expectation model, introduced by Fisher (1911), the expectation formation of agents is based solely on past realizations of the concerned variable and subject to a partial error adjustment if the prediction is not accurate. Formally such a concept could be expressed in what follows (Evans and Honkapohja, 2001, pp. 10):

$$P_{t+1}^e = P_{t-1} + \lambda(P_t - P_{t-1}^e)$$

The agent thus adjusts his prediction of the future with regard to his prediction error in the past with a rate  $\lambda \in [0, 1]$ . Milton Friedman (1968) used this notion of adaptive expectations in his seminal work about the Phillips curve. The Phillips curve, which was an empirical finding by William Phillips (Phillips, 1958), presumes a negative relationship between the inflation rate and the unemployment rate. This relationship was for long time regarded as mechanical and exploited as a policy instrument. Friedman argued that the goal of lowering unemployment under its natural rate with the help of for example monetary policy would, at least in the medium run be offset by agents adjusting their expectations, by past errors, and comprising the higher inflation rate in their bargaining of wages. For two reasons this however didn't go far enough for the proponents of the rational expectation hypothesis (Snowdon and Vane, 2005, p. 227):

1. In times of an accelerating inflation rate an error adjustment mechanism of this sort leads to a systematic underestimation of inflation .
2. Instead of taking all available information into account, as proposed by the rational expectation hypothesis, agents with adaptive expectations only consider past values of the variable in question.



This critique most famously found its expression in the seminal work by Sargent and Wallace (1975) who coined the theory of the “*policy-ineffectiveness proposition*”. Along Sargent and Wallace (1975) every attempt to manipulate the output, for example by monetary policy, would already in short-run be offset by rational agents incorporating the possible effects of taken policy measures into their decision making. The hypothesis of rational expectations was further popularized by Lucas (1976) (this seminal paper became famous under the name “Lucas’ critique”) who argued extending the idea of Muth (1961) that expectations of agents are centered on a unique equilibrium of the economy. Policy measures intending to change the output however would alter this equilibrium (and the expectations) and with it the basis on which this policy decision was taken. Agents in turn would learn the new predictive model and adjust their expectations accordingly. With his critique Lucas directly addressed macroeconomic models which, like the Phillips curve, are based on historic data.

Coinciding with the economic situation in 1970ies, which was characterized by a high inflation and unemployment rate at the same time (due to the oil crisis), the works by Friedman (1968), Sargent et al. (1973) and Lucas (1976) gained significant influence on Economic thinking. Especially Keynesian macroeconomics came under massive pressure, as its results seemed to have become obsolete with the above cited works. Contributions by these early proponents of the rational expectation hypothesis were so influential that today most macroeconomic models comprise assumptions regarding rationality of expectations or unbiasedness of expectations within the core of their model assumptions. This however does not imply that this assumption is not disputed. Articles like for example by Phelps and Taylor (1977), which can be regarded as direct response to works of the above mentioned authors, sought to reestablish the role of Keynesian Economics. Phelps and Taylor (1977) incorporate expectational rationality in their model, but argue that the fact that wages are normally bargained for multiple periods in advance allows monetary policy to still have a stabilizing effect on the economy. Others like Sonnenschein (1973), Debreu (1974) or Mantel (1974) pointed out that individual rationality doesn’t necessarily have implications for aggregate behavior.

In the empirical literature there are multiple, more recent, works which empirically test the hypothesis of rational expectations. Some of them are confirming the hypothesis of rational expectations, as Thomas (1999) or Ang et al. (2007), others are, at least partially, rejecting it, like Mehra (2002), Mankiw and Reis (2002), Roberts (1997) or Baghestani (2009). This study tries to contribute to this empirical stream of the literature.

**Research Question** Using microlevel data from the monthly French household survey (Enquête mensuelle de conjoncture auprès des ménages - ECAMME)<sup>2</sup> this paper addresses the problem field of rationality or unbiasedness of consumer (household) expectations from a different perspective which by now got fairly little attention. It is investigated if some kind of *herd- or flocking-behavior* is identifiable within the expect-

<sup>2</sup>This survey has already been used by other authors to investigate the issue of rational expectations, as for example Gardes and Madre (1991); Gardes et al. (2000) or Gourieroux and Pradel (1986).



tation formation of consumers/households. Herding behavior in this context is defined as a bias towards the consensus of expectations which is assumed to be the mean of all prior expectations within a period. This issue will be discussed in detail later on. The structure of the study is as follows: The traditional probabilistic method, see Theil (1952) and Carlson and Parkin (1975), to quantify survey expectations is extended in a hierarchical Bayesian ordered probit framework to gain individual/cohort-level inflation expectations. Applying a non-parametric test by Bernardt et al. (2006) of herding behavior to the quantified cohort-level inflation expectation estimates finally allows to investigate if consumer expectations of inflation are solely based on the individual assessment (anti-herding) or if they are biased in the direction of a general sentiment or consensus (herding).

The only work, the author is aware of that investigates herding behavior in the context of surveys is the work by Franke et al. (2008). This paper develops a micro-founded model of herding in which agents can switch between two states, optimistic and pessimistic. By means of business survey data from the German ifo and ZEW survey, Franke shows that there is an empirically significant co-movement of agents in terms of transition probabilities between the two states. The paper at hand is different in two ways: First, it addresses the herding behavior of consumers with regard to inflation expectations instead of business sentiment, second, the research question of herding is addressed in a quantitative instead of a qualitative manner as in the paper cited above, thus seeks to answer the question if respondents are biased in the direction of a quantitative consensus.

## 2.2 The Data - Enquête mensuelle de conjoncture auprès des ménages

The Enquête mensuelle de conjoncture auprès des ménages, in the remainder abbreviated by the official acronym ECAMME is a monthly survey conducted by the French statistical office the *Institut National de la Statistique et des Études Économiques* (short INSEE) since 1987. The ECAMME succeeded a row of periodic household sentiment surveys conducted by INSEE since as early as 1958. Although interviews were originally only conducted twice a year, the collection of opinions with regard to the evolution of the French economy as well as buying attitudes were in the focus right from the beginning. In 1968 the frequency was increased to three interview sessions per year. Since 1972 the ECAMME is part of the *Harmonised EU Programme of Business and Consumer Surveys of the European Commission*, which has the goal to standardize survey based economic research within the European Union. From 1987 on, the establishment of the ECAMME as it is known today, the data was finally collected in a monthly manner.

The ECAMME is conducted via telephone interviews with approximately 3300 households per month (until 2006 with the exception of August), which are randomly selected from the official French telephone register. The ECAMME exhibits a basic panel structure, as the households are interviewed in three consecutive months. As will be seen later, this panel structure is however not sufficient for the here envisaged task. A panel



structure thus has to be artificially established using pseudo panelization techniques. The ECAMME survey collects information about the financial situation, employment and the standard of living of the interviewed households as well as their perceptions and expectations regarding various economic variables. In the context of this paper question 5 and 6 within ECAMME are of importance, which ask for the households perceptions and expectations with regard to past and future consumer price developments:

**(Q5)** Do you think that prices in the last twelve months have ... (*Trouvez-vous que, au cours des douze derniers mois, les prix ont...*)

- increased strongly (*fortement augmenté*)
- increased moderately (*modérément augmenté*)
- stagnated (*stagné*)
- decreased (*diminué*)

**(Q6)** In comparison with the last twelve months how do you think the evolution price will be in the next twelve months ... (*Par rapport aux douze derniers mois, quelle sera à votre avis l'évolution des prix au cours des douze prochains mois ...*)

- prices will increase with a higher rate (*elle va être plus rapide*)
- prices will increase with the same rate (*elle va se poursuivre au même rythme*)
- prices will increase with a smaller rate (*elle va être moins rapide*)
- prices will stay the same (*les prix vont rester stationnaires*)
- prices will go down (*les prix vont diminuer*)

For the here conducted research micro data from January 2004 until December 2012 was available, supplied by Réseau Quetelet as a distributor for INSEE.<sup>3</sup> After sorting out non responses, especially in Question 5 and Question 6, and flawed data, this corresponds to all in all 185,945 observations or approximately 1,788 usable interviews per month. The data contains a wide variety of socio-economic information, for example household size, level of education of the head of the household as well as his/her companion, employment status of the head of the household as well as his/her companion, income quartile, age, region, the number of children, the number of persons living in the household et cetera.

ECAMME covers a wide range of the French society: The average participant in the available dataset is however 55.4 years old (st. dev. 16.58), has 0.4 (st.dev. 0.81) children and lives in a household with 2.4 persons (st.dev. 1.3). Of the individuals in the data set 23 % finished primary and 27.5 % finished secondary education. 20.2%

<sup>3</sup>The reader is referred to section 2.A for detailed data references.



sex	education	age		children		hh.size	
		mean	st. dev.	mean	st. dev.	mean	st. dev.
male	primary	68.14	12.47	0.09	0.44	1.98	1.04
	secondary	55.90	15.19	0.32	0.74	2.42	1.22
	post secondary	52.52	14.38	0.41	0.80	2.51	1.23
	tertiary	49.31	15.90	0.51	0.89	2.59	1.31
female	primary	68.99	12.44	0.08	0.43	1.81	1.04
	secondary	55.42	15.92	0.42	0.82	2.48	1.35
	post secondary	50.74	14.44	0.54	0.90	2.71	1.33
	tertiary	45.99	14.34	0.68	0.97	2.76	1.38

Table 2.1: Descriptive Statistics - ECAMME data set (Jan 2004 - Dec 2012)

sex	education	income			
		1st quart.	2nd quart.	3rd quart.	4th quart.
male	primary	42.92	33.59	17.25	6.25
	secondary	17.83	26.15	30.97	25.06
	post secondary	17.4	26.06	35.01	21.53
	tertiary	7.48	11.94	24.17	56.41
female	primary	54.22	30.55	11.72	3.51
	secondary	24.08	28.71	28.87	18.35
	post secondary	22.2	27.53	32.32	17.95
	tertiary	9.88	16.27	26.41	47.44
male		19.38	23.06	27.04	30.53
female		27.36	25.52	24.53	22.58

Table 2.2: Descriptive Statistics - Income - ECAMME data set (Jan 2004 - Dec 2012)

had completed a post-secondary school and 29.2% held a university degree. For some descriptive statistics of the available ECAMME dataset the reader is referred to Table 2.1 and Table 2.2.

## 2.3 A simple non-parametric test for herding

### 2.3.1 The idea

In this section a simple non-parametric test for herding is introduced which was originally developed by Bernardt et al. (2006) to test for a potential biasedness of professional forecasters. It is then shown how this test could be applied to consumer survey data.

It is assumed that consumers intrinsically form expectations over future developments for example of prices in a similar way professional forecasters do, by taking into account every disposable information or evidence (this means their own daily consumption experience, communication with other people, the consumption of media et cetera). The difference of course is that consumers, uncomfortable with economic measures, might have difficulties in quantifying inflation within the next months. This problem is addressed in consumer sentiment or household surveys by asking for qualitative tendencies rather than for exact numbers. Evidence shows that the aggregation of such sentiments delivers a pretty precise picture of the future evolution of prices (Ludvigson, 2004; Mourougane

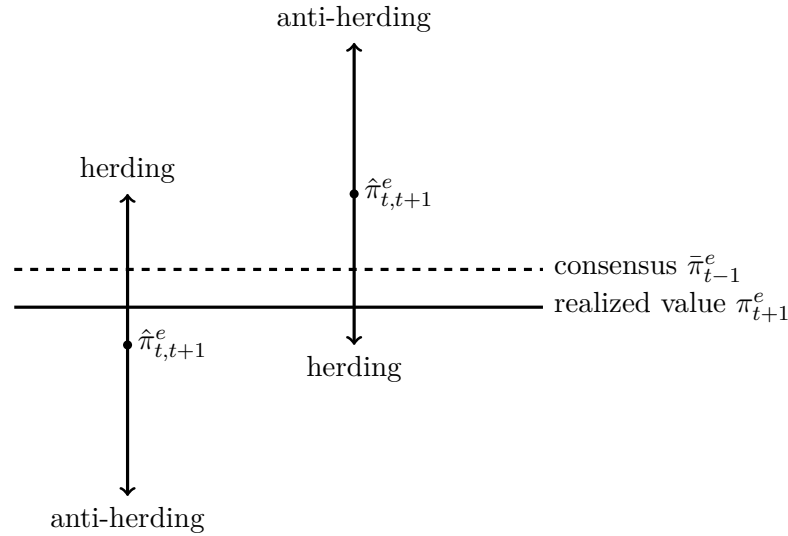


Figure 2.1: Schematic plot of the idea behind the herding test by Bernardt et al. (2006)

and Roma, 2003; Howrey, 2001; Vuchelen, 2004; Vuchelen and Praet, 1984). The problem of quantifying consumer expectations and thus how to gain quantitative forecasts from qualitative consumer expectations collected by surveys (similar to earning forecasts by analysts) on an individual/cohort-level will be addressed in the next section.

For the sake of clarity, the terminology of the literature of finance is adopted: A forecast in this sense is a quantified formulation of expectations over the future development of an economic variable, here inflation  $\pi_{t,t+1}^e$ . A consensus forecast  $\bar{\pi}^e$  is understood as the aggregated and quantified expectation of a reference group, for example other individuals which formulated their expectations at an earlier point in time (later on, the mean of all prior forecasts for the same target value is used as the consensus).<sup>4</sup> A forecast  $\pi_{t,t+1}^e$  at time  $t$  for inflation  $\pi_{t+1}$  at time  $t+1$  is regarded as unbiased if, given all available informations, it equals the median of all posteriors  $\hat{\pi}_{t,t+1}^e$ , this means  $\pi_{t,t+1}^e = \hat{\pi}_{t,t+1}^e$ . Thus, if forecasts are unbiased, there is no reason to assume that they generally tend to be higher or lower than the realized value of the forecasted quantity, this means forecasts should randomly distributed around the consensus. In this sense the probability, given the available information set, that a forecast exceeds or falls short of the realized value  $\pi_{t+1}$  can be assumed to be equally 0.5:  $P(\pi_{t,t+1}^e < \pi_{t+1}) = P(\pi_{t,t+1}^e > \pi_{t+1}) = 0.5$ . If a forecast is however biased it can be assumed that it deviates from the median of posteriors. Therefore the probabilities that the realized values of the forecasted quantities

<sup>4</sup>Consensus forecasts find widespread usage, especially in applied Economics. They are regularly published by newspapers or (central) banks to inform readers or clients what professionals in the financial industry or in research think about the future evolution of economic variables. There is a large amount of literature showing that the simple combination of forecasts by averaging can increase the accuracy significantly (see for example (Bates and Granger, 1969; Batchelor, 2001; Jones, 2014)).

will be above or below the forecast, also change. In terms of herding, a bias will be one towards the extant consensus of a reference group (the mean of prior expectations/forecasts with regard to the same variable of [all] other individuals). If an agent herds and his forecast lies above the consensus then the probability that his forecast will be too low is more than one half. Vice versa the probability that a forecast will exceed the realized value given a bias towards the consensus where the forecast lies below the consensus is equally more than one half. Thus, seen from the opposite perspective and more formal: If the agent herds toward the consensus  $\bar{\pi}_{t,t+1}^e$  and his posterior  $\hat{\pi}_{t,t+1}^e$  is above the consensus, he will choose a forecast  $\pi_{t,t+1}^e \in \{\bar{\pi}_{t,t+1}^e, \hat{\pi}_{t,t+1}^e\}$ . So if  $\pi_{t,t+1}^e > \bar{\pi}_{t,t+1}^e$ , it will exceed the realized value with probability less than one half, as  $\pi_{t,t+1}^e < \hat{\pi}_{t,t+1}^e$  and  $P(\pi_{t+1} < \pi_{t,t+1}^e) < P(\pi_{t+1} < \hat{\pi}_{t,t+1}^e) = \frac{1}{2}$ . Herding can be assumed if the two following conditional probabilities fulfill the following conditions:

$$P(\pi_{t+1} < \pi_{t,t+1}^e | \bar{\pi}_{t,t+1}^e < \pi_{t,t+1}^e, \pi_{t,t+1}^e \neq \pi_{t+1}) < \frac{1}{2} \quad (2.1)$$

$$P(\pi_{t+1} > \pi_{t,t+1}^e | \bar{\pi}_{t,t+1}^e > \pi_{t,t+1}^e, \pi_{t,t+1}^e \neq \pi_{t+1}) < \frac{1}{2} \quad (2.2)$$

Anti-herding on the other hand, thus a bias away from the consensus forecast, is fulfilled if:

$$P(\pi_{t+1} < \pi_{t,t+1}^e | \bar{\pi}_{t,t+1}^e < \pi_{t,t+1}^e, \pi_{t,t+1}^e \neq \pi_{t+1}) > \frac{1}{2} \quad (2.3)$$

$$P(\pi_{t+1} > \pi_{t,t+1}^e | \bar{\pi}_{t,t+1}^e > \pi_{t,t+1}^e, \pi_{t,t+1}^e \neq \pi_{t+1}) > \frac{1}{2} \quad (2.4)$$

A schematical display of the idea behind the herding test can be found in Figure 2.1.

### 2.3.2 The Test Statistics

With regard to the idea presented in Section 2.3.1 Bernardt et al. (2006) construct the following test statistics which is also used here. The conditioning events  $z_t^+$ , if  $\pi_{t,t+1}^e > \bar{\pi}_{t,t+1}^e$ , and  $z_t^-$ , if  $\pi_{t,t+1}^e < \bar{\pi}_{t,t+1}^e$ , are defined. According to this the indicator functions,

$$\gamma_t^+ = 1 \quad \text{if } z_t^+ \quad \text{otherwise } \gamma_t^+ = 0 \quad (2.5)$$

$$\gamma_t^- = 1 \quad \text{if } z_t^- \quad \text{otherwise } \gamma_t^- = 0 \quad (2.6)$$

are constructed. The variables

$$\delta_t^+ = 1 \quad \text{if } z_t^+ \quad \text{AND } \pi_t^e > \pi_t \quad \text{otherwise } \delta_t^+ = 0 \quad (2.7)$$

$$\delta_t^- = 1 \quad \text{if } z_t^- \quad \text{AND } \pi_t^e < \pi_t \quad \text{otherwise } \delta_t^- = 0 \quad (2.8)$$

indicate overshooting and undershooting with regard to the realized value. The mean of both conditional probabilities from above measures if the forecasts overshoot/undershoot the realized variable in the same direction in which they overshoot/undershoot the consensus forecast.

$$S(z_t^-, z_t^+) = \frac{1}{2} \left[ \frac{\sum_t \delta_t^+}{\sum_t \gamma_t^+} + \frac{\sum_t \delta_t^-}{\sum_t \gamma_t^-} \right] \quad (2.9)$$



$S(z_t^-, z_t^+) < \frac{1}{2}$  indicates a bias to the consensus (herding) while  $S(z_t^-, z_t^+) > \frac{1}{2}$  indicates a bias away from the consensus (anti-herding). A derivation of the second central moment of the test statistics as well as a discussion of possible robustness issues can be found in Appendix 2.B and 2.C<sup>5</sup> respectively (along Bernardt et al. (2006)).

### 2.3.3 Comparisons with other approaches to test the REH

The herding test outlined above stands in line with traditional tests of the REH in the literature. Generally one can differentiate between quantitative and qualitative tests. For the former category individual-level and pooled data can be used. In the case the data stems from a qualitative consumer survey like the ECAMME, however a quantification procedure as outlined in the next section has to be undertaken beforehand. Qualitative tests, like the one presented in what follows, can however be directly applied to qualitative survey data.

**Quantitative tests of the REH** Tests of the rational expectations hypothesis along Muth (1961) traditionally comprise two equivalent procedures:<sup>6</sup> A test for unbiasedness and a test for efficiency. Unbiasedness can be evaluated formally by estimating the following equation:

$$\pi_{t+1} = \alpha + \beta \pi_{t,t+1}^e + \xi_{t+1}$$

Like above  $\pi_{t+1}$  corresponds to the realized inflation rate in period  $t + 1$  while  $\pi_{t,t+1}^e$  is the expectations thereof formed in period  $t$ . If the joint hypothesis  $H_0 : (\alpha, \beta) = (0, 1)$  cannot be rejected one can assume statistical unbiasedness in the Muthian sense. This means a systematic bias to over- or underestimate cannot be assumed (Forsells and Kenny, 2002). The herding test outlined above belongs to the family of unbiasedness tests.

The second standard test for the rational expectation hypothesis addresses the efficient use of information in the expectation formation process. It thus is evaluated if the information used in the expectation formation process is orthogonal to the prediction error.

$$\pi_{t+1} - \pi_{t,t+1}^e = \delta + \phi \Omega_t + \xi_{t+1}$$

Here  $\Omega_t$  corresponds to the information set (compare to Section 2.1) which was available to the agents when forming their expectations in period  $t$  with regard to the realization of the variable in question in period  $t + 1$ .  $\Omega_t$  is assumed to be a set of macroeconomic variables which the agent takes into account when forming his expectations over the future. A significant parameter  $\phi$  indicates that the influence of variables in the information set on the concerned variable (in this context inflation) has been systematically over- or underestimated respectively. (Forsells and Kenny, 2002)

<sup>5</sup>In Appendix 2.C it is shown that the herding test by Bernardt et al. (2006) is robust to commonly unforecasted shocks differentiating it from simple correlation.

<sup>6</sup>For an outline of Muth's rationality conditions the reader is referred to Section 2.1



	j
i	$n_{ij}$

Table 2.3: Contingency table - expectations  $j$  vs. perceptions  $i$ 

**Qualitative tests of the REH** As far as qualitative tests of the rational expectation hypothesis are concerned, a test proposed by Gourieroux and Pradel (1986) and applied by Gardes et al. (2000) to the same data set as used in this study should be mentioned here. Assuming that a survey contains a qualitative forward looking (expectation) and qualitative backward looking (perception) question with regard to the same variable, a contingency table like Table 2.3 can be compiled. This table contains the number of respondents  $n_{ij}$  who opted for category  $j$  in the expectation question in period  $t$  and for category  $i$  in the perception question in period  $t + 1$ . If  $n$  is the total number of respondents, one can then compute the share of respondents whose expectations and subsequent perceptions are equivalent  $p_{jj} = n_{jj}/n$  (corresponding to the values on the diagonal of the contingency table) as well as the fraction of respondents (for each combination of  $j$  and  $i$ ) whose expectations and subsequent perceptions are different:  $p_{ij} = n_{ij}/n$  (corresponding to the values off the diagonal in the contingency table). The hypothesis of rational expectations is satisfied if and only if for each category  $j$  the diagonal is strictly greater than all other elements in the same column, thus if:

$$p_{jj} > \max_i p_{ij}$$

For the same data set as used in this study Gardes et al. (2000) find that along the rationality test proposed by Gourieroux and Pradel (1986) only a part of the survey population is in line with the rationality condition outlined above.

## 2.4 Quantifying Inflation Expectations

Unlike to the forecasts of professional analysts, the method described in the previous section cannot directly be applied to consumer expectation data collected by surveys. Quantified consumer expectations with regard to inflation are not, or just rarely, available. Interviewees participating in a consumer survey like ECAMME might be unfamiliar to give a concrete quantitative answer how for example prices will evolve in the upcoming twelve months. Therefore consumer surveys normally ask for tendencies rather than precise numbers, by proposing qualitative response options. Before the above described test can be applied, estimation techniques have to be used to transform the qualitative

answers of survey participants into quantitative forecasts.<sup>7</sup>

Roughly spoken there are two different approaches to quantify qualitative survey data: The regression approach which roots can be tracked back to Anderson (1952), Pesaran (1985, 1987) as well as Pesaran and Weale (2006b) on the one hand, and the probability approach which was initially developed by Theil (1952) and Carlson and Parkin (1975) respectively and thus is often denominated by the latter as the *Carlson-Parkin* approach on the other hand. In the study at hand a modification of the probability or Carlson-Parkin approach will be used: Along the paper by Kaiser and Spitz (2002) the Carlson-Parkin method will be interpreted in the context of an ordered probit/logit estimation. As will be seen in the following discussion, such a modification of the probability approach provides two crucial advantages for the here envisioned task when compared to the regression approach:

1. it bases to a lesser extent on strict assumptions,
2. the various sociodemographic information available in the micro data of the ECAMME survey can be exploited to derive individual-(cohort-)level inflation expectations when the probability approach is interpreted as an ordered probit/logit model and estimated in a hierarchical bayesian framework.

Corresponding to questions 5 and 6 in ECAMME (see Section 2.2), an expectation horizon of twelve months is used in the notation within this section.<sup>8</sup> This was taken into account when the estimations were done and the test statistic was applied respectively.

### 2.4.1 Regression approach

The regression approach in its baseline setting, as presented by Pesaran and Weale (2006b), assumes that there are only two different answering options in a survey regarding perceived and expected inflation and that each of the  $N$  participants  $j$  had a specific expected inflation rate  $\pi_{j,t,t+1}^e$  in mind when surveyed at time  $t$ . If one would then group the participants as  $U_{t+1}$  and  $D_{t+1}$  depending on whether they expected rising (denoted as  $+$ ) or falling prices (denoted as  $-$ ), one could write:

$$\tilde{\pi}_{t,t+1}^e = \sum_{j \in U_{t+1}} w_{j,t+1}^+ \pi_{j,t,t+1}^{e+} + \sum_{j \in D_{t+1}} w_{j,t+1}^- \pi_{j,t,t+1}^{e-} \quad (2.10)$$

Unfortunately specific values of  $\pi_{j,t,t+1}^e$  are not available for household surveys. Pesaran therefore supposes that inflation expectations of households, may they indicate a lower or

<sup>7</sup>Since 2004 ECAMME contains questions for the quantitative perceptions and expectations of inflation. Analyzing this data shows that respondents in aggregate have a good intuition of price developments as far as tendencies are concerned, but are rather bad at giving quantitative estimates. The concerned variables are full of outliers and frequently state totally exaggerated values. The monthly averages of these quantitative estimations by respondents lie systematically several percentage points above the actual inflation rate. A potential use of these variables is however briefly discussed in Section 2.7.2

<sup>8</sup>Before 2004, when the survey was adjusted to the standard of the harmonized European consumer surveys program, participants were asked for a perception/expectation horizon of six months. Therefore not the whole monthly data set of ECAMME could be used.

higher rate of inflation, fluctuate around a fixed moment with independently distributed error terms  $\epsilon_i$  for each individual with mean 0 and variance  $\sigma^2$ . Under this assumption the expected inflation rates can be expressed as:

$$\pi_{j,t,t+1}^{e+} = \alpha + \epsilon_{j\alpha} \quad (2.11)$$

$$\pi_{j,t,t+1}^{e-} = -\beta + \epsilon_{j\beta} \quad (2.12)$$

with  $\alpha, \beta > 0$ . If the variances  $\sigma_{alpha}^2$  and  $\sigma_{beta}^2$  are sufficiently small and follow appropriate shaped distributions in order that  $\pi_{j,t,t+1}^{e+} > 0$  and  $\pi_{j,t,t+1}^{e-} < 0$  respectively  $\forall j, t$  then one can rewrite equation (2.10) to:

$$\tilde{\pi}_{t,t+1}^e \approx \alpha \sum_{j \in U_{t+1}} w_{j,t}^+ - \beta \sum_{j \in D_{t+1}} w_{j,t+1}^- \quad (2.13)$$

$$\tilde{\pi}_{t,t+1}^e \approx \alpha U_{t+1}^e - \beta D_{t+1}^e \quad (2.14)$$

The crucial and at the same time very strong assumption by Pesaran is that inflation perceptions are formed in the same manner as inflation expectations: parameters  $\alpha$  and  $\beta$  can be estimated by means of appropriate regression techniques with  $\pi_t$  on the fractions  $U_t$  and  $D_t$  regarding inflation perceptions and then used to calculate a time series of quantitative values for  $\pi_{t,t+1}^e$ . This means for example for a linear scenario and the here used twelve month horizon in both directions that  $\pi_t = \alpha U_t + \beta D_t + \epsilon_t$  is estimated for the actual inflation rate (which in the standard monthly form gives the evolution of consumer prices between  $t - 12$  and  $t$ ), where the parameters  $\hat{\alpha}$  and  $\hat{\beta}$  are then used to calculate the expected inflation rate by  $\hat{\pi}_{t,t+12} = \hat{\alpha} U_t + \hat{\beta} D_t$  (Pesaran and Weale, 2006b).

There are various extensions of the baseline model. A modification proposed by Pesaran and Weale (2006b) comprises an adjustment to an assumed asymmetry between the perception of rising and falling prices, where it is supposed that the former outweighs the latter:  $\pi_t = (\alpha U_t + \beta D_t) / (1 - \lambda U_t) + \epsilon_t$ . Another modification includes AR(2) autoregressive errors from the OLS version of the model in order to correct for autocorrelation of the error terms:  $\pi_t = (\alpha U_t + \beta D_t + \phi_1 \hat{\epsilon}_{t-1} + \phi_2 \hat{\epsilon}_{t-2}) / (1 - \lambda U_t) + \epsilon_t$ . Along the reviewed literature this procedure is regarded as disputable (Curto Millet, 2009; Nardo, 2003), but might serve to gain a good fit between estimated expected inflation and actual inflation by accounting for some kind of eventual error correction heuristic applied by agents when uttering their expectations and perceptions. Accounting for the equational form, both models are estimated by means of non-linear least squares estimations.

The regression approach however has two characteristics which renders it problematic for the here envisioned task: First, perceptions of price changes are assumed to be unbiased; second, it is assumed that inflation perceptions are formed along the same mechanisms as inflation expectations; third, and more important for the envisioned task, it does not allow to control for heterogeneity within participants.

### 2.4.2 The Carlson-Parkin Approach

The Carlson-Parkin or probability approach chooses a different way to quantify qualitative expectation data from a survey: Namely it assumes that the fraction of each answering option corresponds to a maximum likelihood estimate in the context of the aggregate density function with regard to inflation expectations (Forsells and Kenny, 2002). Simply put, the perceived inflation rate is anchored to an assumed probability distribution function using the qualitative survey data of inflation expectations. To demonstrate this approach it is referred to Berk (1999) who also discusses a survey with five answering categories like it is the case in the forward looking inflation question in the ECAMME (Q6).

The perceived inflation rate is anchored to an assumed probability distribution via thresholds: It is for example assumed that the expected inflation rate follows a Gaussian distribution.<sup>9</sup> From the data, by the fraction respondents chose each response category, so called threshold values are calculated. At these cut-off points people change one answering option for another. These points are then scaled to the perceived inflation rate. The perceived inflation is the assumed rate of the increase of prices people have in mind when choosing one of the answering categories in the survey with regard to the price developments in the upcoming twelve months. In this respect two intervals are important in the baseline Carlson-Parkin approach:

- $\delta_t$  is an interval in which consumers perceive no change in prices. This interval is called the *indifference limen*.
- $\mu_t$  signifies an interval around the perceived rate of inflation  $\pi_{j,t}^p$  above/below which consumers experience or better expect an increasing/decreasing rate of inflation  $\pi_{j,t+1}^e$ .

It is important to note that both thresholds are symmetric, a shortcoming which will be addressed later on by the ordered probit interpretation of the Carlson-Parkin method. In the baseline model it is further assumed that the perceived rate of inflation  $\pi_{j,t}^p$  is equal for all individuals  $j$  and can thus be denoted as  $\pi_t^p$ . In the simplest scenario it is assumed that the perceived inflation rate is the latest published inflation rate. This is of course disputable, since individuals may have a different consumption attitude and might thus perceive price changes differently. Since ECAMME, like all standardized European household surveys, also contains a question how respondents perceived inflation in the last twelve months (Q5), it is easy to also estimate quantified values of the perceived inflation rate by the Carlson-Parkin method. The threshold model with  $\delta_t$  and  $\mu_t$  can be written as (Maag, 2009):

$$\begin{aligned} \pi_{j,t}^e &< -\delta_t : \text{the prices will decrease } (S_1) \\ -\delta_t &\leq \pi_{j,t}^e < \delta_t : \text{the prices will stay the same } (S_2) \\ \delta_t &\leq \pi_{j,t}^e < \pi_t^p - \mu_t : \text{the prices will rise at a lower rate } (S_3) \end{aligned}$$

<sup>9</sup>This is the standard assumption but was for example criticized by Maddala (1991). Berk (1999) for example tests the Carlson-Parkin approach under different distributional assumptions.

$$\begin{aligned}\pi_t^p - \mu_t &\leq \pi_{j,t}^e < \pi_t^p + \mu_t : \text{prices will rise at the same rate } (S_4) \\ \pi_{j,t}^e &< \pi_t^p + \mu_t : \text{prices will rise at a faster rate } (S_5)\end{aligned}$$

The probabilities for these events can be easily estimated by the response shares. If it is assumed that the expected inflation rate follows a normal distribution  $\pi_{j,t}^e \sim N(\pi_t^e, (\sigma_t^e)^2)$  and that  $\Phi()$  is the cumulative distribution function of the normal distribution, the threshold model from above can be rewritten in terms of probabilities:

$$s_t^1 = P(\pi_{j,t}^e < -\delta_t) = \Phi\left(\frac{-\delta_t - \pi_t^e}{\sigma_t}\right) \quad (2.15)$$

$$s_t^2 = P(-\delta_t \leq \pi_{j,t}^e < \delta_t) = \Phi\left(\frac{\delta_t - \pi_t^e}{\sigma_t}\right) - \Phi\left(\frac{-\delta_t - \pi_t^e}{\sigma_t}\right) \quad (2.16)$$

$$s_t^3 = P(\delta_t \leq \pi_{j,t}^e < \pi_t^p - \mu_t) = \Phi\left(\frac{\pi_t^p - \mu_t - \pi_t^e}{\sigma_t}\right) - \Phi\left(\frac{\delta_t - \pi_t^e}{\sigma_t}\right) \quad (2.17)$$

$$s_t^4 = P(\pi_t^p - \mu_t \leq \pi_{j,t}^e < \pi_t^p + \mu_t) = \Phi\left(\frac{\pi_t^p + \mu_t - \pi_t^e}{\sigma_t}\right) - \Phi\left(\frac{\pi_t^p - \mu_t - \pi_t^e}{\sigma_t}\right) \quad (2.18)$$

$$s_t^5 = P(\pi_{j,t}^e \geq \pi_t^p + \mu_t) = 1 - \Phi\left(\frac{\pi_t^p + \mu_t - \pi_t^e}{\sigma_t}\right) \quad (2.19)$$

Using the inverse cumulative distribution allows to rewrite this system of equations which makes it solvable for the unknowns  $\pi_t^e$ ,  $\sigma_t$ ,  $\delta_t$  and  $\mu_t$ .  $\pi_t^p$  is assumed to be given by the most recently published inflation rate in the baseline model.

$$\begin{aligned}G_t^1 &= \Phi^{-1}(s_t^1) = \frac{-\delta_t - \pi_t^e}{\sigma_t} \\ G_t^2 &= \Phi^{-1}(1 - s_t^5 - s_t^4 - s_t^3 - s_t^2) = \frac{-\delta_t - \pi_t^e}{\sigma_t} \\ G_t^3 &= \Phi^{-1}(1 - s_t^5 - s_t^4 - s_t^3) = \frac{\delta_t - \pi_t^e}{\sigma_t} \\ G_t^4 &= \Phi^{-1}(1 - s_t^5 - s_t^4) = \frac{\pi_t^p - \mu_t - \pi_t^e}{\sigma_t} \\ G_t^5 &= \Phi^{-1}(1 - s_t^5) = \frac{\pi_t^p + \mu_t - \pi_t^e}{\sigma_t}\end{aligned}$$

The unknown variables can easily be found by combining the equations from above. The mean expected inflation rate would for example be:

$$\pi_t^e = \pi_t^p \frac{G_t^2 + G_t^3}{G_t^2 + G_t^3 - G_t^4 - G_t^5}$$

### 2.4.3 Quantification with Ordered Probit

Reconsidering the approach by Carlson-Parkin it can be formulated as a threshold model which could equivalently be estimated by the use of an ordered probit regression (Kaiser and Spitz, 2002). Again it is assumed that respondent  $j$  within a survey bases his decision which answer on the scale to choose on a subliminal threshold ranking. The estimation of the model by the use of ordered probit however allows for asymmetric thresholds ( $\mu_1, \mu_2, \mu_3, \mu_4$ ). This seems more appropriate as the decrease/increase of prices is likely to be perceived with a different sensitivity. The expected change between perceived and future inflation (the forward looking question Q6 asks for the change of inflation, while the backward looking question Q5 asks for the change of prices; this will be discussed in more detail later on) is now denoted as  $\Delta\pi_t^e = \pi_t^e - \pi_t^p$ .

$$\begin{aligned}\pi_t^e - \pi_t^p &< \mu_t^1 \\ \mu_t^1 &\leq \pi_t^e - \pi_t^p < \mu_t^2 \\ \mu_t^2 &\leq \pi_t^e - \pi_t^p < \mu_t^3 \\ \mu_t^3 &\leq \pi_t^e - \pi_t^p < \mu_t^4 \\ \pi_t^e - \pi_t^p &\geq \mu_t^4\end{aligned}$$

This implies along before:<sup>10</sup>

$$\begin{aligned}P(S_1) &= P(\Delta\pi^e \leq \mu_1) = P(0 \leq -\Delta\pi^e + \mu_1) \\ P(S_2) &= P(\Delta\pi^e \leq \mu_2) - P(\Delta\pi^e \leq \mu_1) = P(0 \leq -\Delta\pi^e + \mu_2) - P(0 \leq -\Delta\pi^e + \mu_1) \\ P(S_3) &= P(\Delta\pi^e \leq \mu_3) - P(\Delta\pi^e \leq \mu_2) = P(0 \leq -\Delta\pi^e + \mu_3) - P(0 \leq -\Delta\pi^e + \mu_2) \\ P(S_4) &= P(\Delta\pi^e \leq \mu_4) - P(\Delta\pi^e \leq \mu_3) = P(0 \leq -\Delta\pi^e + \mu_4) - P(0 \leq -\Delta\pi^e + \mu_3) \\ P(S_5) &= 1 - P(\Delta\pi^e \leq \mu_4) = 1 - P(0 \leq -\Delta\pi^e + \mu_4)\end{aligned}$$

As before, it is assumed that the expected inflation rate follows a normal distribution.  $\Phi()$  is the cumulative distribution function.

$$\begin{aligned}S_1 &= P(\Delta\pi^e < \mu_1) = \Phi\left(\frac{-\Delta\pi^e + \mu_1}{\sigma}\right) \\ S_2 &= P(\mu_1 \leq \Delta\pi^e < \mu_2) = \Phi\left(\frac{-\Delta\pi^e + \mu_2}{\sigma}\right) - \Phi\left(\frac{-\Delta\pi^e + \mu_1}{\sigma}\right) \\ S_3 &= P(\mu_2 \leq \Delta\pi^e < \mu_3) = \Phi\left(\frac{-\Delta\pi^e + \mu_3}{\sigma}\right) - \Phi\left(\frac{-\Delta\pi^e + \mu_2}{\sigma}\right) \\ S_4 &= P(\mu_3 \leq \Delta\pi^e < \mu_4) = \Phi\left(\frac{-\Delta\pi^e + \mu_4}{\sigma}\right) - \Phi\left(\frac{-\Delta\pi^e + \mu_3}{\sigma}\right) \\ S_5 &= P(\mu_4 \leq \Delta\pi^e) = 1 - \Phi\left(\frac{-\Delta\pi^e + \mu_4}{\sigma}\right)\end{aligned}$$

<sup>10</sup>For the sake of clarity the notation was simplified in the equations below:  $t$  and  $j$  subscripts were omitted.

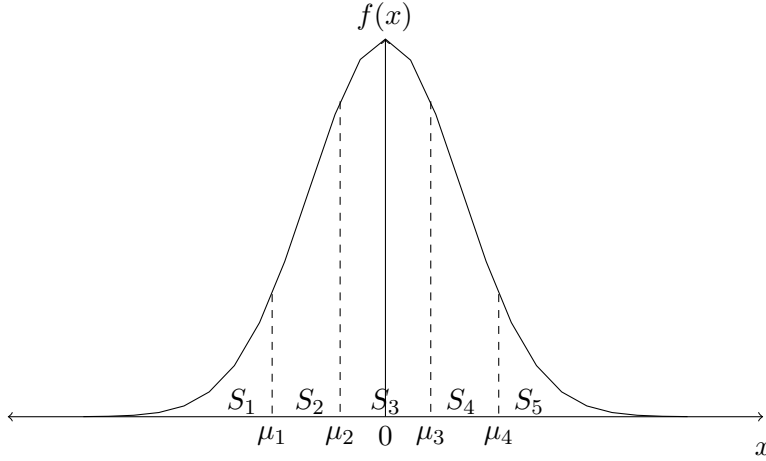


Figure 2.2: Threshold model with a standard normal distribution

(2.20)

This basic model can, along Kaiser and Spitz (2002), easily be extended to one which can be applied to repeatedly conducted surveys. They assume that the expected variable (Kaiser and Spitz (2002) seek to quantify quarterly revenues of firms by survey data) depends on a constant term  $\beta$  and a disturbance term  $\epsilon$ . Let  $I_{jt}$  be a dummy variable for the participation in the survey of individual  $j$  at time  $t \in 1...T$ , then the equation for inflation within the ordered probit model can be specified as  $\pi_{jt} = \sum_{t=1}^T \beta_t I_{jt} + \epsilon_{jt}$ . Along Kaiser and Spitz (2002), the threshold model, adapted for the here envisaged purpose, is:

$$\pi_{jt}^* = \begin{cases} S_1 & \text{if } \pi_{jt} = \sum_{t=1}^T \beta_t I_{jt} + \epsilon_{jt} < \mu_1 \\ S_2 & \text{if } \mu_1 \leq \pi_{jt} = \sum_{t=1}^T \beta_t I_{jt} + \epsilon_{jt} < \mu_2 \\ S_3 & \text{if } \mu_2 \leq \pi_{jt} = \sum_{t=1}^T \beta_t I_{jt} + \epsilon_{jt} < \mu_3 \\ S_4 & \text{if } \mu_3 \leq \pi_{jt} = \sum_{t=1}^T \beta_t I_{jt} + \epsilon_{jt} < \mu_4 \\ S_5 & \text{if } \pi_{jt} = \sum_{t=1}^T \beta_t I_{jt} + \epsilon_{jt} \geq \mu_4 \end{cases} \quad (2.21)$$

Along the assumptions by Kaiser and Spitz (2002),  $\beta_t$  would then correspond to the expected change in inflation (or, as will be seen later, if applied to question Q5, to the perceived inflation rate). The basic formulation of the threshold model, which only incorporates dummy variables  $I_{jt}$  that signal participation, would correspond to the quantification method of Carlson-Parkin with constant threshold values. To however include individual- and time-specific characteristics in the specification would allow for individual- and time-specific threshold values. This suggests to include the various sociodemographic information contained in the ECAMME data set as explanatory variables in the ordered probit estimation.

Kaiser and Spitz (2002) further suggest to interact the time dummy variables with, in their context, firm level dummies to gain firm specific expected revenue growth rates for

each quarter. With an average of 1788 individuals per period (after cleaning the data) and without any panel structure, such a model is for obvious reasons not estimable. To overcome this problem this paper extends the approach suggested by Kaiser and Spitz (2002): Using a self-organizing Kohonen map (Kohonen, 1982), a pseudo panel is constructed, which allows to follow the inflation perceptions/expectations of different groups over the whole time period available in the dataset. Then the approach described above is implemented in the context of an ordinal MCMC Hierarchical Bayesian Model with a probit link function which allows to estimate the parameter estimate  $\beta$  and thus the expected change of inflation on a cohort-level. The approach is outlined in the next two sections.

## 2.5 Construction of a pseudo panel

The panel-structure problem is addressed by forming a synthetic or pseudo panel. The first author who used this technique to overcome a lack of panel structure was Deaton (1985). He uses variables that are supposed not to change over time such as sex and birth cohorts to group the survey population. This paper however pursues a neural network technique to construct pseudo panels, introduced by Gardes et al. (1996) as it exhibits three crucial advantages:

1. It allows for an inclusion of more comprehensive and precise sociodemographic information when building the pseudo panel. Deaton's technique applied to the ECAMME dataset with variables as sex (2 categories), region (22 categories) and birth cohorts (3 categories; the survey participants are for example manually grouped into three cohorts: a) under 30 years, b) between 30 and 55 years, c) over 55 years) would result into 132 cohorts. In the neural network approach the number of cohorts can be freely chosen with respect to the overall survey population. An inclusion of much more sociodemographic information becomes possible. The information content of continuous variables as for example income (such a variable unfortunately is absent in the dataset of ECAMME after 2003) does not have to be artificially reduced by grouping them into different classes, as it would be necessary when using Deaton's approach. They can be used directly in the construction of the pseudo panel.
2. A pseudo panel constructed by the neural network technique is better balanced. The ECAMME data set available exhibits huge imbalances as far as for example the variables sex and region are concerned. The survey is mainly addressed to the head of the household. As a consequence, in around 60% of all cases the gender variable (sex) is male. Similarly, most of the interviewed participants which are randomly chosen from the official French telephone register come from the metropolitan area of Paris (region11), reflecting the fact that around 20% of the French population are living in one of the eight departments of Paris and its surroundings. Interacting these variables into cohorts as Deaton suggests would result in unbalanced cohort sizes, eventually leading to heteroscedasticity in the estimation. This is an issue



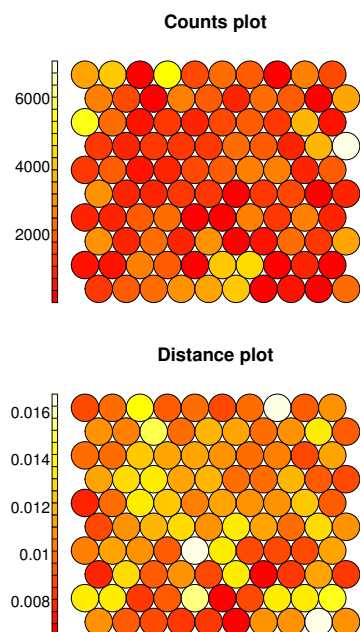


Figure 2.3: Plot of the self organizing Kohonen map

which does not exist when using the neural network approach by Gardes et al. (1996).

3. Cottrell and Gaubert (2007) show that constructing cohorts via neural networks results in a lower within cohort and a higher between cohort variance than when using the technique by Deaton. This is crucial feature when constructing a pseudo panel.

In this paper, along the work by Gardes et al. (1996) and, Cottrell and Gaubert (2007), self-organizing Kohonen maps (Kohonen, 1982) are thus applied to group the participants in the repeated cross sections into synthetic cohorts: sociodemographic variables describing participants in the dataset as sex, birth year (birthyr), region, citysize, education (educ), childs (number of children), fracwork (the percentage of people in a household who have a job), revquart (the income quartile of the household), work regime (the regime of the employment), finan (the perceived financial situation of the household), spouse, nbpers (number of persons living in the household) and occup (occupation) are presented to the neural network in overall hundred runs. The Kohonen map was constructed on a  $10 \times 10$  hexagonal plane over the whole dataset. Then after it was checked which of the cohorts are available in all time periods. The number of cohorts which are available over the whole time period of the dataset corresponds to 59. To achieve a clean separation of cohorts only the four individuals with the lowest unit to cell distances within each cohort and time period were used. Figure 2.3 displays the counts for

each cell (cohort) over the whole data set and the average distance measures for each cell (cohort). For the construction of the Kohonen map the “kohonen” R-package was used (Wehrens and Buydens, 2007).<sup>11</sup>

## 2.6 Estimating cohort-level inflation with ordinal HB-MCMC

Interacting time and cohort dummy variables within an ordered probit estimation in order to gain group/cohort-level estimates of the expected change in inflation rate as suggested by Kaiser and Spitz (2002) is, as already mentioned above, not a good idea in the context of this work. It results into singularity issues and over-specification. The here chosen approach is to split up the estimation into a fixed effect part, containing several socioeconomic variables, and a random effects part which allows to estimate cohort-specific intercepts for the time dummy variable corresponding to a cohort-specific estimate of the expected change of inflation. In this respect an ordinal Hierarchical (or Mixed) Bayes Markov Chain Monte Carlo method seems most appropriate as it is widely used for example in marketing studies (*conjoint analysis*) to investigate consumer level reactions to certain product characteristics.

**Bayesian estimation, what is it about:** In Bayesian estimation methods the parameter estimates are regarded as random variables while in Maximum likelihood estimations they are viewed as fixed maximizers. This means that all possible values for a parameter estimate  $\theta$  are compared and ranked. To do so, its distribution conditional on the data  $x$ ,  $p(\theta|x)$  has to be known. This distribution is called the *posterior* distribution which is determined by the *likelihood*  $p(x|\theta)$  and the *prior* distribution  $p(\theta)$  along  $p(\theta|x) = p(x|\theta)p(\theta)/p(x)$ . The prior  $p(\theta)$  is provided by the user.  $p(x)$  is regarded as a normalizing constant, the so called evidence. The estimate of the parameter  $\theta$  could then be computed by solving the integral  $\hat{\theta} = E_{\theta|x}[\theta] = \int \theta p(\theta|x_1, x_2, \dots, x_n) d\theta$ . At this point however the normalization constant or evidence is missing. It could be calculated by solving the integral  $p(x) = \int p(x|\theta)p(\theta) d\theta$ . This integral is however only solvable analytically if the *likelihood* and the *prior* form a conjugate pair. If this is not the case, Markov Chain Monte Carlo (MCMC) methods can be used. With MCMC the posterior distribution is evaluated point by point until a constant is reached. In this context the *Metropolis-Hastings algorithm* is normally applied. It randomly draws samples from a proposed distribution. Iteratively points leading to a higher probability are accepted while points leading to an equal or lower probability are rejected. Thereby regions of high probability are iteratively explored. Out of the accepted sample, the parameter (point estimate) can then be estimated by integrating over the posterior distribution (Orbanz, 2013).

The Hierarchical Bayes Markov Chain Monte Carlo method provides the following advantages for there envisioned task:

1. It allows for heterogeneity without having to estimate a model cohort by cohort.

<sup>11</sup>For another application of the Kohonen algorithm the reader is referred to Chapter 5.



2. It can handle relatively small amounts of cohort-level data and still gives good estimates as it borrows information from the whole population to gain individual-level or here cohort-level estimates.
3. One can run very complex estimations. The inclusion of explanatory variables is only limited by hardware restrictions.

### 2.6.1 Specification

The estimation done in this paper were conducted with the R-package “MCMCglmm” by Hadfield (2010). The setup was as follows:

$$Y_{tj} = X_{tj}\beta + Z_{tj}b_{tj} + e_{tj} \quad (2.22)$$

where  $X$  is the design matrix for the fixed effects with parameters  $\beta$ , and  $Z$  is the design matrix for the random part with parameters  $b$ .  $j$  denotes the  $j^{th}$  cohort. The following specification was used for the fixed effects:

$$X_{tj}\beta =$$

$$\begin{aligned} & \beta_1 SEX_{tj} + \beta_2 EDUC_{ti} + \beta_3 REGION_{tj} + \beta_4 AGE_{tj} + \beta_5 CHILDS_{tj} \\ & + \beta_6 REVQUART_{tj} + \beta_7 REGION_{tj} + \beta_8 CITYSIZE_{tj} + \beta_9 WORKREGIME_{tj} \\ & + \beta_{10} FRACWORK_{tj} + \beta_{11} ECON\_PERT_{tj} + \beta_{12} ECON\_EXPT_{tj} + \beta_{13} FINANT_{tj} \end{aligned}$$

- *SEX* ... is a categorical variable in the survey denoting the sex of the interviewed head of the household
- *EDUC* ... is a categorical variable in the survey regarding the education of the respondent
- *REGION* ... is a categorical variable in the survey regarding the region of residence of the respondent
- *AGE* ... the age of the respondent
- *CHILDS* ... number of children below 14 years living in the same household as the respondent
- *REVQUART* ... is a categorical variable describing the income quartile to which a household belongs
- *CITYSIZE* ... is a categorical variable describing the size of the city in which the household has its residence
- *FRACWORK* ... a numeric variable between 0 and 1 describing the percentage of people within the household with a job
- *ECON\_PER/ECON\_EXP* ... categorical variables describing the perception-/expectations of households with regard to the French economy



- *FINAN* ... categorical variables describing the financial situation as perceived by the household itself

The random effect part is specified as follows:

$$Z_{tj}b_{tj} = b_{tj}ID_{tj} * WAVE_{tj} \quad (2.23)$$

- *WAVE* ... dummy variable for the respective survey wave. In this part the WAVE-specific random intercept is estimated.
- *ID* ... is the variable denoting the cohort ID.
- $ID_{tj} * WAVE_{tj}$  ... This part allows the cohort-level random intercepts to be estimated.

Along Berk (1999) the expected changes in inflation are calculated in two steps: As outlined in Section 2.4.2, the expected inflation in the Carlson-Parkin approach is calculated on the basis of a perceived inflation rate. For the sake of simplicity in the literature the perceived inflation rate is normally assumed to be the latest published inflation rate. This assumption is however debatable. As the ECAMME contains a question which asks the respondents for their inflation perceptions (see Section 2.2, question Q5), one can estimate a perceived inflation along the same method on which one can then base the estimated expected inflation rate. The model described above is thus estimated for two dependent variables:

1. the perceived inflation given by the 4-category variable  $I_{tj}^p$  (see Section 2.2, Q5) – the perception estimate (random intercept) is further on denoted as  $b_{1tj}$ ;
2. the expected inflation rate given by the 5-category variable  $I_{tj}^e$  (see Section 2.2, Q6) – the expectation estimate (random intercept) is further on denoted as  $b_{2tj}$ ;

## 2.6.2 Settings and Diagnostics

The priors for the fixed effect structure ( $B$ ), the variance structure of the residuals ( $R$ ) and the variance structure of the random part ( $G$ ) are specified as follows to run the ordinal Hierarchical Bayesian estimation,

$$\begin{aligned} B &\sim N(0, \text{diag}(\text{dim}(X)) * 1e10) \\ R &\sim W^{-1}(V = 1, nu = 1) \\ G &\sim W^{-1}(V = \text{diag}(N), nu = N + 2) \end{aligned}$$

where  $N$  denotes the number of cohorts and  $\text{dim}(X)$  denotes the dimension of the fixed effects model matrix.  $W^{-1}$  denotes the Inverse-Wishart distribution. The R structure priors are set along (Hadfield, 2010, Table 1) for ordinal regressions.

The estimations were run with 300,000 iterations each and with the thinning and burning parameters set to 50 and 60,000 respectively. The estimation of both models on a computer with a i7-2640M processor and 8GB of memory took around 36 hours.

	post. mean	low. 95 perc. conf. lim.	up. 95 perc. conf. lim.	effect. sample	pMCMC	signif.
age	0.002	-0.000	0.005	5038.271	0.103	
econ_per1	3.594	2.890	4.253	3595.727	0.000	***
econ_per2	3.167	2.627	3.755	3573.543	0.000	***
econ_per3	3.229	2.692	3.805	3482.898	0.000	***
econ_per4	3.688	3.123	4.243	3433.360	0.000	***
econ_per5	4.364	3.806	4.918	3359.485	0.000	***
econ_exp.1	-0.323	-0.527	-0.117	4535.841	0.003	**
econ_exp.2	0.205	0.028	0.371	4800.000	0.023	*
econ_exp.3	-0.014	-0.122	0.094	4800.000	0.811	
econ_exp.4	-0.035	-0.091	0.025	4800.000	0.227	
region21	-0.021	-0.269	0.226	5465.550	0.870	
region22	0.133	-0.106	0.386	4498.877	0.278	
region23	0.154	-0.072	0.388	5069.825	0.190	
region24	0.148	-0.070	0.358	4503.697	0.184	
region25	0.065	-0.180	0.313	4800.000	0.609	
region26	0.050	-0.182	0.285	6130.088	0.685	
region31	0.101	-0.110	0.310	4800.000	0.352	
region41	0.221	0.009	0.450	4800.000	0.049	*
region42	0.098	-0.141	0.318	4800.000	0.412	
region43	0.042	-0.233	0.287	4800.000	0.735	
region52	-0.015	-0.221	0.206	4597.017	0.887	
region53	0.020	-0.194	0.217	4800.000	0.859	
region54	0.007	-0.220	0.256	4564.842	0.942	
region72	0.150	-0.060	0.365	4800.000	0.161	
region73	0.074	-0.142	0.279	4800.000	0.501	
region74	-0.064	-0.338	0.238	4800.000	0.666	
region82	0.240	0.041	0.439	4800.000	0.022	*
region83	0.341	0.113	0.600	4800.000	0.006	**
region91	0.077	-0.142	0.322	4800.000	0.513	
region93	0.319	0.107	0.517	4800.000	0.003	**
region94	0.528	0.018	1.047	4800.000	0.049	*
citysize.1	-0.062	-0.196	0.077	4545.323	0.380	
citysize.2	-0.017	-0.181	0.126	4800.000	0.829	
citysize.3	0.125	-0.045	0.273	4800.000	0.122	
citysize.4	0.061	-0.086	0.200	4800.000	0.393	
citysize.5	-0.071	-0.206	0.073	4588.974	0.322	
citysize.6	0.038	-0.120	0.179	4800.000	0.612	
citysize.7	-0.114	-0.262	0.053	4800.000	0.168	
citysize.8	0.126	-0.038	0.291	4800.000	0.142	
educ.1	-0.227	-0.311	-0.143	4800.000	0.000	***
educ.2	-0.116	-0.184	-0.051	5031.206	0.002	**
educ.3	-0.148	-0.205	-0.089	5045.272	0.000	***
childs	0.029	-0.010	0.065	4800.000	0.139	
fracwork	0.032	-0.092	0.167	4800.000	0.620	
sex2	0.297	0.221	0.372	4800.000	0.000	***
revquart.1	-0.086	-0.168	-0.002	4800.000	0.043	*
revquart.2	-0.029	-0.095	0.039	5078.338	0.381	
revquart.3	-0.046	-0.100	0.014	4800.000	0.120	
workregime1	0.098	-0.058	0.243	4632.493	0.214	
workregime2	0.189	-0.092	0.489	4800.000	0.203	
workregime9	-0.124	-0.273	0.040	4800.000	0.122	
finan2	0.227	-0.213	0.674	5532.799	0.334	
finan3	0.469	0.028	0.926	5524.299	0.040	*
finan4	0.593	0.109	1.019	5509.132	0.008	**
finan5	0.878	0.353	1.411	6949.582	0.002	**
cutpoint.1	2.266	2.155	2.373	133.383		
cutpoint.2	3.805	3.688	3.912	131.167		
cutpoint.3	5.083	4.964	5.193	129.275		

Table 2.4: Perception estimation - Fixed effects [Signif. codes: 0 '\*\*\*', 0.001 '\*\*', 0.01 '\*', 0.05 '· 0.1']

	post. mean	low. 95 perc. conf. lim.	up. 95 perc. conf. lim.	effect. sample	pMCMC	signif.
age	0.003	0.001	0.006	4800.000	0.025	*
econ_per1	3.535	2.855	4.211	4800.000	0.000	***
econ_per2	3.640	3.073	4.209	4800.000	0.000	***
econ_per3	3.557	2.994	4.103	3068.690	0.000	***
econ_per4	3.618	3.049	4.163	3009.613	0.000	***
econ_per5	3.672	3.102	4.215	3011.347	0.000	***
econ_exp.1	-1.257	-1.456	-1.056	4800.000	0.000	***
econ_exp.2	0.037	-0.132	0.208	4800.000	0.685	
econ_exp.3	0.056	-0.051	0.165	4552.892	0.315	
econ_exp.4	-0.048	-0.102	0.009	4338.935	0.097	.
region21	0.125	-0.128	0.369	4800.000	0.305	
region22	-0.052	-0.289	0.183	4048.983	0.677	
region23	0.122	-0.108	0.340	4800.000	0.305	
region24	0.142	-0.068	0.357	4800.000	0.175	
region25	0.151	-0.104	0.385	4800.000	0.225	
region26	0.023	-0.192	0.263	4034.229	0.836	
region31	-0.101	-0.295	0.114	4246.428	0.343	
region41	-0.207	-0.417	0.012	5002.027	0.063	.
region42	-0.258	-0.477	-0.026	5631.955	0.027	*
region43	-0.011	-0.282	0.241	4800.000	0.927	
region52	0.121	-0.078	0.324	4272.908	0.247	
region53	0.246	0.043	0.452	4800.000	0.015	*
region54	0.060	-0.166	0.296	4800.000	0.622	
region72	-0.022	-0.224	0.187	4800.000	0.850	
region73	0.128	-0.086	0.335	4186.523	0.230	
region74	0.298	0.022	0.593	4800.000	0.039	*
region82	0.129	-0.058	0.316	4176.320	0.189	
region83	0.206	-0.033	0.438	4800.000	0.095	.
region91	0.088	-0.133	0.319	5067.657	0.446	
region93	0.127	-0.069	0.331	4105.664	0.213	
region94	0.227	-0.238	0.724	4800.000	0.372	
citysize.1	-0.087	-0.221	0.049	4800.000	0.212	
citysize.2	-0.027	-0.178	0.119	4800.000	0.720	
citysize.3	0.178	0.025	0.329	4800.000	0.021	*
citysize.4	-0.035	-0.178	0.100	4800.000	0.621	
citysize.5	-0.028	-0.160	0.100	4888.152	0.679	
citysize.6	-0.033	-0.174	0.125	4800.000	0.663	
citysize.7	0.070	-0.072	0.232	4800.000	0.386	
citysize.8	-0.054	-0.217	0.101	4800.000	0.511	
educ.1	0.099	0.020	0.188	4259.146	0.020	*
educ.2	-0.058	-0.129	0.005	4800.000	0.092	.
educ.3	0.049	-0.004	0.110	4800.000	0.086	.
childs	-0.018	-0.053	0.019	4800.000	0.334	
fracwork	0.001	-0.126	0.122	4800.000	0.977	
sex2	-0.038	-0.110	0.037	4799.234	0.320	
revquart.1	-0.080	-0.160	0.001	4800.000	0.054	.
revquart.2	-0.045	-0.114	0.018	4800.000	0.172	
revquart.3	-0.014	-0.070	0.040	4384.701	0.641	
workregime1	0.156	0.016	0.296	4130.997	0.027	*
workregime2	-0.062	-0.338	0.215	4800.000	0.659	
workregime9	-0.052	-0.195	0.083	4800.000	0.462	
finan2	-0.355	-0.844	0.104	4800.000	0.140	
finan3	-0.234	-0.730	0.224	4800.000	0.334	
finan4	-0.228	-0.718	0.236	4800.000	0.353	
finan5	0.092	-0.452	0.612	4800.000	0.737	
cutpoint.1	2.675	2.605	2.755	232.070		
cutpoint.2	3.430	3.353	3.506	221.452		
cutpoint.3	6.051	5.968	6.137	235.715		

Table 2.5: Expectation estimation - Fixed effects [Signif. codes: 0 '\*\*\*', 0.001 '\*\*', 0.01 '\*', 0.05 '·', 0.1]

The crucial results of the estimation process are the posterior distributions of the random intercepts. Integrating over the posterior distributions of the random intercepts supplies the “BLUPs” (linear unbiased predictors) or “conditional modes” and thus the individual level parameter estimates. The two parameters estimates per period and cohort can then be used to calculate the perceived and expected inflation rate respectively for each cohort in each period. The calculation of the quantified measure for the perceived and the expected inflation will be discussed in the next section.

**Convergence** In order to check convergence of the estimated chains the Heidelberger and Welch’s convergence diagnostic (Heidelberger and Welch, 1981) is applied to both estimations. The diagnostic consists of two parts: first a Cramer-von-Mises statistic is applied to check the null hypothesis that the sample values are drawn from a stationary distribution. Therefore this test is at first conducted on the whole sample and then successively the first 10%, 20% and so on of the chain are cast aside until the  $H_0$  is accepted. If the  $H_0$  cannot be accepted before 50% are cast aside, the diagnostic fails. In this case one would have to rerun the estimation with more iterations in order to achieve stationary posterior distributions. In a second part of the diagnostic the 95% confidence intervals for the means of the fractions of the posterior distributions for which the  $H_0$  of stationarity was accepted are computed. In the case the ratio between the half width or radius of this confidence interval and the estimated mean is lower than a target value the sample size is regarded as being too small to estimate the mean with sufficient precision. The target value for the ratio of halfwidth to the sample mean was set to be 0.3 and the p-value was set to 0.05.

		stationarity test (pct. passed)	start itera- tion	combined p-value (Stouf- fer)	halfwidth test (pct. passed)	avg. mean	avg. halfwidth
Perceptions	fixed	0.982	98.778	0.036	0.964	0.417	0.004
	random	0.993	98.778	0.989	0.933	0.011	0.018
Expectations	fixed	1	62.091	0.088	0.964	0.319	0.004
	random	0.993	62.091	1	0.922	0.009	0.018

Table 2.6: Heidelberger/Welch Stationarity Test and Halfwidth Test

The results of the Heidelberger and Welch’s convergence diagnostic are displayed in Table 2.6. The convergence diagnostic states that the estimated posterior distributions are stationary in more than 99% of all cases. The Halfwidth Test passed in more than 92% in all cases, indicating that the models were run with a sufficient amount of iterations and that the means of the posterior distributions have been estimated with adequate accuracy for nearly all parameter estimates. Only a negligible proportion of posterior distributions thus failed to converge.



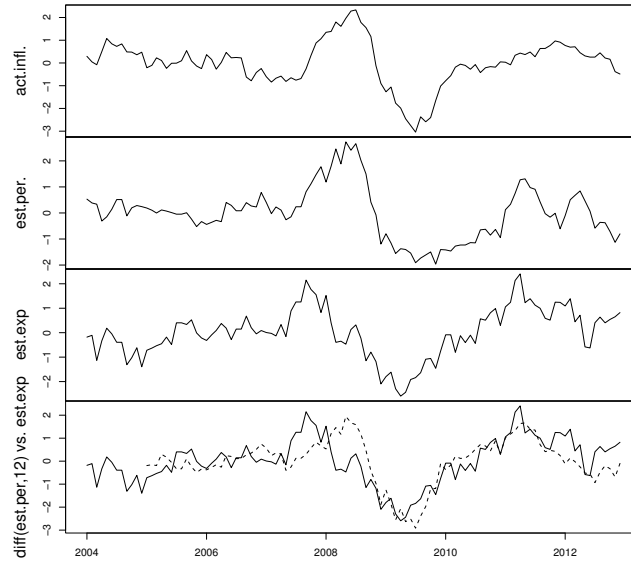


Figure 2.4: Raw estimates of perceptions and expectations; differentiated perceptions vs. expectations - Jan 2004 to Dec 2012

## 2.7 Estimation results and computation of the perceived/-expected inflation rate

### 2.7.1 Discussion of the raw perception/expectation estimates

Figure 2.4 compares the actual inflation rate (first graph) with the perception estimate ( $b_{1tj}$ , second graph) and the expectation estimate ( $b_{2tj}$ , third graph): The second and the third graph display monthly averages over all cohorts for the random intercept estimates of the two (perception/expectations) hierarchical MCMC ordered probit models presented in the previous section. The synchronous behavior of the perception estimate with the actual inflation rate, even though both measures are on a different scale, is apparent on the first glance. This is verified by Figure 2.5: Computing the correlation between the actual inflation rate and the perception estimate with different lags not only shows that respondents have a very good intuition for past price changes but also perceive these price changes promptly after they occur: The highest correlation between the two time series is at a lag of zero and one (this means where actual inflation rate from  $t - 1$  is compared with the perception estimate from  $t$ ). However as far as the expected inflation rate is concerned the highest correlation with the actual inflation rate is not at a lag of 12 months as would be implied by question Q6 but at a lag of six months. However for the application of the test statistic this paper follows the wording

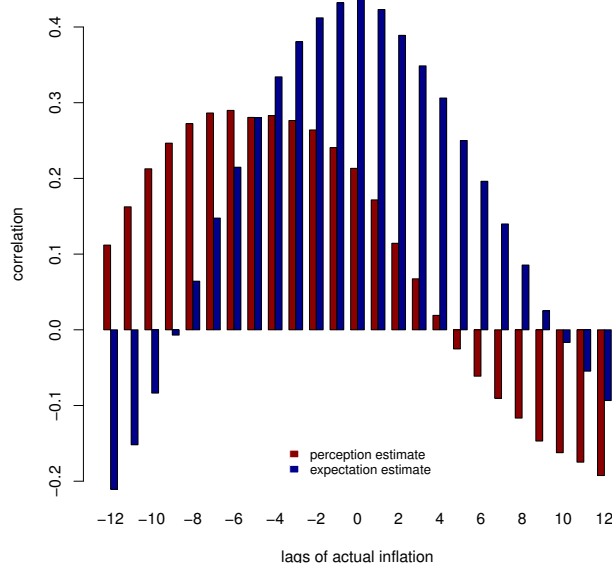


Figure 2.5: Correlation - Perceptions vs. actual Inflation - Jan 2004 to Dec 2012

of the question asked to the survey respondents. It has to be again underlined that the perception/expectation estimate solely bases on the posterior distributions of the cohort/period-level random intercepts estimated with the model with Q5 and Q6 (see Section 2.2) as the dependent variable respectively as outlined in the last section. The inflation rate itself is not part of this estimation in any form.

Comparing the graph of the actual inflation rate (graph 1) and the expectation estimate (graph 3) in Figure 2.4, such a striking synchrony cannot be observed. Rather the expectation estimate, which corresponds to the mean of posterior distributions of cohort/period-level random intercepts of estimation 2 with variable Q6 (see Section 2.2) as dependent variable, seems to precede the actual inflation by a few months. This assertion is however misleading. To see that, one has to take a closer look at the wording of the questions Q5, about the perceived past inflation, and question Q6, about the expected future inflation (see Section 2.2): The backward looking question asks for the “price change” in the last twelve months. This corresponds to the price change of the consumer basket as surveyed by the national statistics office in terms of percentages between today and the same period (month) one year before. The forward looking question Q6, in contrast, asks for the evolution of prices in the next twelve months compared with the last twelve months. Response options here are for example: the prices will rise with a *higher* rate, with the *same* rate, with a *smaller* rate and so on. One could thus say that the backward looking question (Q5) asks for the derivative of

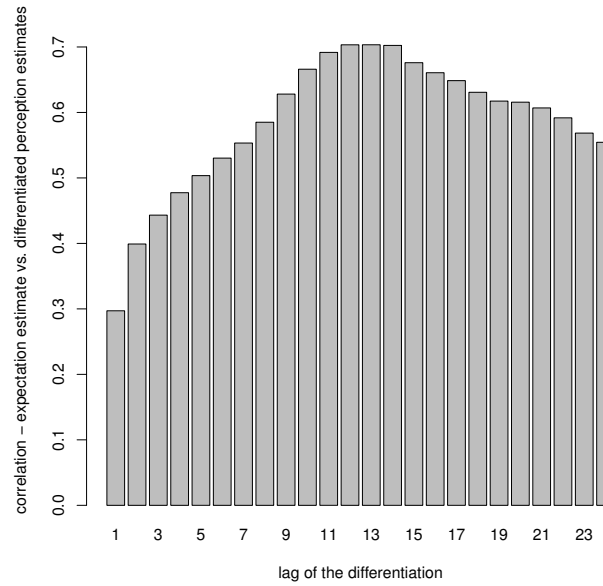


Figure 2.6: Correlation - Expectations vs. differentiated Perceptions - Jan 2004 to Dec 2012

consumer price of the first order, while the forward looking question (Q6) asks for the second order derivative of prices (the expected change of price changes). This difference in wording is also reflected in the estimates for perceptions and expectations computed by the method outlined in the last section. The fourth graph in Figure 2.4 displays the expectation estimate and the perception estimate, where the latter was transformed by twelve month differences as suggested by the wording of the question to get the two series on the same order: by this procedure we get a time series reflecting the perceived changes of prices changes (inflation) in the last twelve months. Figure 2.6 displays the correlation between the expectation estimate on the one hand and the perception estimate with different difference lags on the other hand. According to the wording of question Q6 the correlation is the highest when the perception estimate is transformed by a twelve months difference.

Corresponding to these assertions, the technique to compute estimates for the perceived and the expected inflation rates which are comparable to the actual inflation rate and thus practical for the application of the non-parametric test for herd behavior described in section 2.3 is outlined in the next subsection.

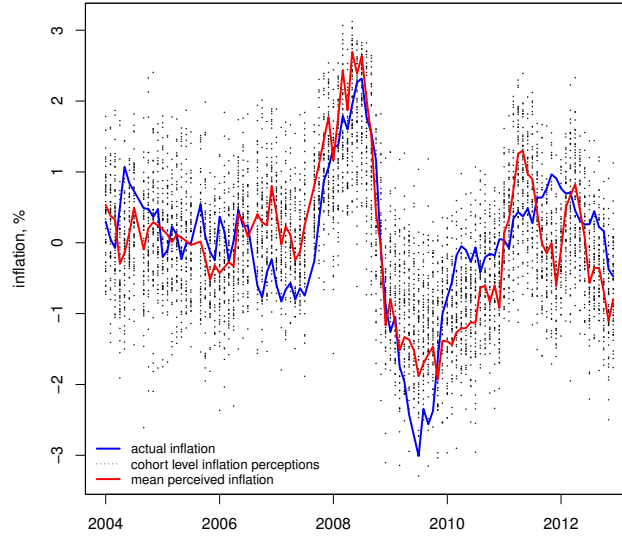


Figure 2.7: Cohort-level inflation perceptions and actual inflation - Jan 2004 to Dec 2012

### 2.7.2 Deriving the expected inflation rate

As discussed in the last subsection the perception estimate is closely correlated to the actual inflation rate: Respondents have a good intuition of price changes in terms of tendencies even if they occurred quite recently. The actual inflation rate and the perception estimate as well as the expectation estimate are however on different scales. This problem is solved by standardizing all measures to  $\mu = 0$  and  $\sigma = 1$ . This procedure was conducted for each cohorts time series separately. In the case of the expectation estimate, the pseudo panel time series for each cohort was integrated with a twelve months difference before the procedure, to get the different variables (perception and expectation estimate, actual inflation) to the same order and re-transformed by taking the twelve months difference afterwards. Figure 2.7 gives an impression about the distribution of cohort-level inflation perceptions for each cohort in the data set and over all periods.

The perceived inflation rate computed by normalization of  $b_{1tj}$  (see section 2.6) is denoted as  $\pi_{tj}^p$ . Along the wording of question Q6 and what was shown in the last subsection it is assumed that the expectation estimate reflects the change of the perceived inflation between  $t$  and  $t + 12$ . The expected inflation rate  $\pi_{tj}^e$  can thus be calculated by:

$$\pi_{tj}^e = \pi_{tj}^p + b_{2tj} \quad (2.24)$$

$b_{1tj}$  and  $b_{2tj}$  here denote the respective wave/cohort-level intercepts from estimation 1

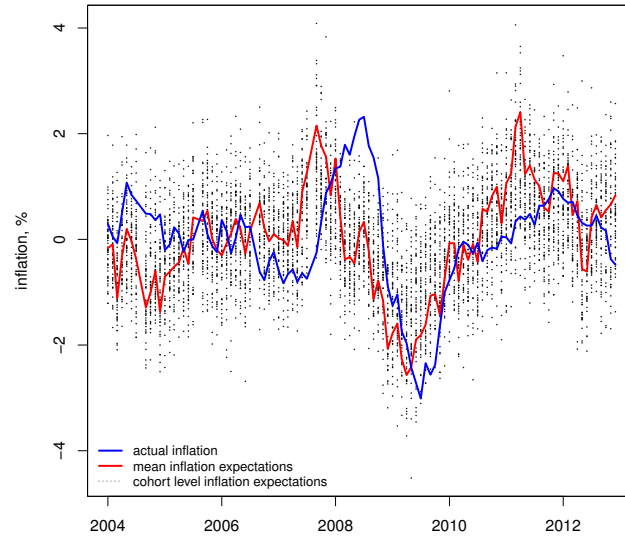


Figure 2.8: Cohort-level inflation expectations and actual inflation - Jan 2004 to Dec 2012

(perceptions) and 2 (expectations; see Section 2.6) respectively. In order not to lose information of the posterior distributions in the application of the test statistic not the point estimates (the integrals) of the posterior distributions were used but the entire posterior distributions themselves. Nevertheless the same procedures as described above (standardization etc.) were applied before. How this was done will be outlined in more detail in the next section. Figure 2.8 displays the distribution of cohort-level inflation expectations in comparison with the actual inflation rate and the mean of the expected inflation rate. Figures 2.10 and 2.11 in the Appendix display charts of the perceived and the expected inflation rates for each cohort against the actual inflation rate. The procedure outlined above pursues the goal to make the data applicable to the herding test statistics. To obtain quantitative values of the perceived and expected inflation in different context which correspond to the scale of the actual inflation rate one could simply scale the cohort-level perception estimates in each period to the latest published actual inflation rate. The expected inflation rate can then be computed, analogously to above, by adding the expectation estimate to the perceived inflation rate in  $t$  to get the expected inflation rate for  $t + 12$ . This again has to be done on a period/cohort-level.

Another idea would be, to use the quantitative questions with regard to inflation perceptions/expectations and to compare them with the qualitative answers in order to calculate thresholds which can then be used to estimate the model. This would however mean to fix the thresholds for cohorts over time, since the values stated by

most individuals are often not really realistic (this was already discussed above). In the ordered probit framework used here the thresholds are estimated implicitly within the model.

## 2.8 Modifying the test statistics for an application with posterior distributions

With the estimated cohort level inflation expectations at hand, computed along the method described above, the test statistics outlined in Section 2.3 could be applied. As however mentioned already in the last section instead of point estimates the whole posterior distributions of the hierarchical bayesian estimation procedure for the expectations and perceptions respectively should be used. For each cohort the sample size of the posterior distribution in each months is 4,500. All in all this results in a data set with a little less then 27 million observations. If one thus wants to compare the posterior distribution of one cohort with the posterior distribution of all other cohorts within one month, one would have to compare a distribution with a sample size of 4,500 with a sample of  $56 \times 4,500 = 252000$  (all in all there are 57 cohorts). This would imply that one would have to look at  $1.134 \times 10^9$  combinations. This procedure would have to be repeated for every cohort and every period. The test statistics is however supposed to be applied quarterly: The distributions of all cohorts should be compared with those of all other cohorts in the current and all previous months within a a quarter. For a cohort in the third month within a cohort one would have to compare  $3 \times 56 \times 4500 \times 4500 = 3.402 \times 10^9$ . This procedure would have also be repeated for every cohort within every month and every quarter. This is computationally not feasible. We therefore apply a rank sum test in the style of the Wilcoxon test to conduct these computations.  $A$  and  $B$  are samples with sample sizes  $m$  and  $n$  respectively. The probability to draw a certain value of  $A$  and  $B$  respectively is thus  $1/m$  and  $1/n$  respectively. Assume that the two samples are combined and ordered. The indexes of these combined ordered sample of the values of  $A$  and  $B$  are the respective ranks. Be  $r_1 < r_2 < \dots < r_m$  of  $A$  within the combined sample. The probability that a draw from  $B$  is smaller than  $r_i$  equals the number of all smaller values of  $B$  divided by the sample size  $n$ . The number of smaller values in  $A$  and  $B$  is  $r_i - 1$  of which  $i - 1$  ( $r_1, r_2, \dots, r_{i-1}$ ) values stem from sample  $A$ . Therefore:

$$P(A > B | A = r_i) = \frac{1}{n}(r_i - 1 - (i - 1)) = \frac{1}{n}(r_i - i) \quad (2.25)$$

$$P(A > B) = \sum_{i=1}^m P(A > B | A = r_i) P(A = r_i) = \frac{1}{mn} \sum_{i=1}^m (r_i - i) \quad (2.26)$$

Similarly one can find a solution for conditional probabilities of the form outlined in section 2.3. Assume there is a third sample  $C$  with  $k$  observations. One can again form a combined set of  $A$  with  $B$  ( $\{A, B\}$ ) and  $A$  with  $C$  respectively ( $\{A, C\}$ ). The ranks of

A within  $\{A, B\}$  are  $r_i^1$  and the ranks of A within  $\{A, C\}$  are  $r_j^1$ .

$$P(A > B | A > C) = \frac{\frac{1}{mnk} \sum_{i=1}^m \sum_{j=1}^m (r_i^1 - i)(r_j^2 - j)}{\frac{1}{mk} \sum_{j=1}^m (r_j^2 - j)} \quad (2.27)$$

With formula (2.27) at hand the conditional probabilities of the test statistic as outlined in section 2.3 can accurately be computed in a very fast manner. If  $r_l^3$  are the ranks of C in the combined set  $\{A, C\}$  then the variance of the test statistic  $S$  (as outlined in the Appendix) is accordingly:

$$Var(S) = \frac{1}{16} \left[ \frac{1}{n \times \sum_{j=1}^m (r_j^2 - j)} + \frac{1}{n \times \sum_{l=1}^m (r_l^3 - l)} \right] \quad (2.28)$$

ECAMME asks the respondents for the inflation rate twelve months ahead. Therefore, according to the wording of question Q6 (see Section 2.2) the quarterly inflation rate from twelve months ahead, after the date of the interview (interview *wave*), is used as the actual or target inflation rate which participants are asked to forecast and then, along the test statistic, compared with the current individual-level inflation expectations and consensus expectations (or with their posterior distributions).

The test statistic is applied quarterly: The posterior distributions of each cohort are on the one hand compared with the posterior distributions of all other cohorts in the same month and all other previous months within the respective quarter and on the other hand with the concerning actual quarterly inflation from twelve months ahead. This means in contrast to the standard herding test by Bernardt et al. (2006) there is no concrete consensus value, the information of the entire posterior distribution is exploited. This paper investigates the expectations (in the form of their posterior distributions) of agents (cohorts) in interaction with the expectations (posterior distributions) of all other agents (cohorts). The variance of the test statistics is computed accordingly.

## 2.9 Conclusion

Table 2.7 and Figure 2.9 represent the results of the herding test: As outlined in Section 2.3, a  $S$  value of below 0.5 would indicate herding behavior. A value  $S$  of above 0.5 on the other hand indicates anti-herding behavior.

The hypothesis that there is herding behavior within consumer expectations towards the consensus can be rejected in all periods. More over most periods exhibit a value  $S$  significantly greater than 0.5 which indicates anti-herding. Anti-herding corresponds, as already mentioned before, to an overweighting of individual information compared to public information (the consensus or the expectations of other people). Herding on the other hand can be considered as the overweighting of public information.

In this respect it is very interesting to note that in the years 2007/2008 when the economic crisis started the value of the test statistic is the lowest over all sample periods. This indicates, that respondents within this time were more influenced by public information than in other time periods. This result corresponds to intuition: The collapse

Date (year.quarter)	$Pr(F_t > E_t z_t^+)$	$Pr(F_t < E_t z_t^-)$	S	S.E.
2004.Q1	0.669	0.660	0.665	0.000
2004.Q2	0.767	0.560	0.663	0.000
2004.Q3	0.808	0.432	0.620	0.000
2004.Q4	0.734	0.556	0.645	0.000
2005.Q1	0.796	0.494	0.645	0.000
2005.Q2	0.847	0.441	0.644	0.000
2005.Q3	0.616	0.683	0.650	0.000
2005.Q4	0.613	0.703	0.658	0.000
2006.Q1	0.532	0.776	0.654	0.000
2006.Q2	0.399	0.858	0.629	0.000
2006.Q3	0.406	0.858	0.632	0.000
2006.Q4	0.890	0.348	0.619	0.000
2007.Q1	0.993	0.075	0.534	0.000
2007.Q2	0.998	0.029	0.514	0.000
2007.Q3	0.969	0.158	0.564	0.000
2007.Q4	0.339	0.838	0.588	0.000
2008.Q1	0.019	0.999	0.509	0.000
2008.Q2	0.001	1.000	0.500	0.000
2008.Q3	0.001	1.000	0.500	0.000
2008.Q4	0.310	0.836	0.573	0.000
2009.Q1	0.879	0.326	0.603	0.000
2009.Q2	0.974	0.130	0.552	0.000
2009.Q3	0.972	0.144	0.558	0.000
2009.Q4	0.981	0.137	0.559	0.000
2010.Q1	0.963	0.179	0.571	0.000
2010.Q2	0.984	0.119	0.552	0.000
2010.Q3	0.970	0.181	0.575	0.000
2010.Q4	0.988	0.119	0.553	0.000
2011.Q1	0.802	0.506	0.654	0.000
2011.Q2	0.396	0.872	0.634	0.000
2011.Q3	0.649	0.657	0.653	0.000
2011.Q4	0.596	0.723	0.659	0.000
2012.Q1	0.352	0.907	0.630	0.000
2012.Q2	0.138	0.981	0.560	0.000
2012.Q3	0.438	0.859	0.649	0.000
2012.Q4	0.549	0.782	0.666	0.000

Table 2.7: Results - test statistics

of the Lehman Brothers investment bank in September 2008, which is regarded as the start of US subprime crisis as well as the global financial crisis created a large turmoil in the banking sector and the stock market and thus received intensive worldwide media coverage. Lehman Brothers was the third biggest investment bank in the United States before it filed bankruptcy. It thus was soon clear that these events would have global implications. It seems intuitive that in the context of such dramatic developments agents would attribute more weight to public information, even if it is contradictory to what they perceive in their daily life. The fact that the test statistic is at its lowest around the third quarter of 2008 supports this interpretation.

This general result is supported by Rülke and Tillmann (2011) who find that members of the Federal Open Market Committee exhibit a strong anti-herding behavior when uttering their inflation forecasts. This phenomenon is especially strong within non-voting members of the FOMC. Rülke and Tillmann (2011) explain their results as some kind of strategic behavior with regard to monetary policy. This interpretation might of course not be directly applied to the case of household expectations, but the findings of the paper at hand might base on similar mechanisms. Being interviewed by a public entity, respondents might use there answers to implicitly transport their opinion about economic policy related to price changes eventually trying to push it into a certain direction.

One objection might be that the results strongly depend on the purchasing power of respondents. This means that a respondent with lower income will classify a price

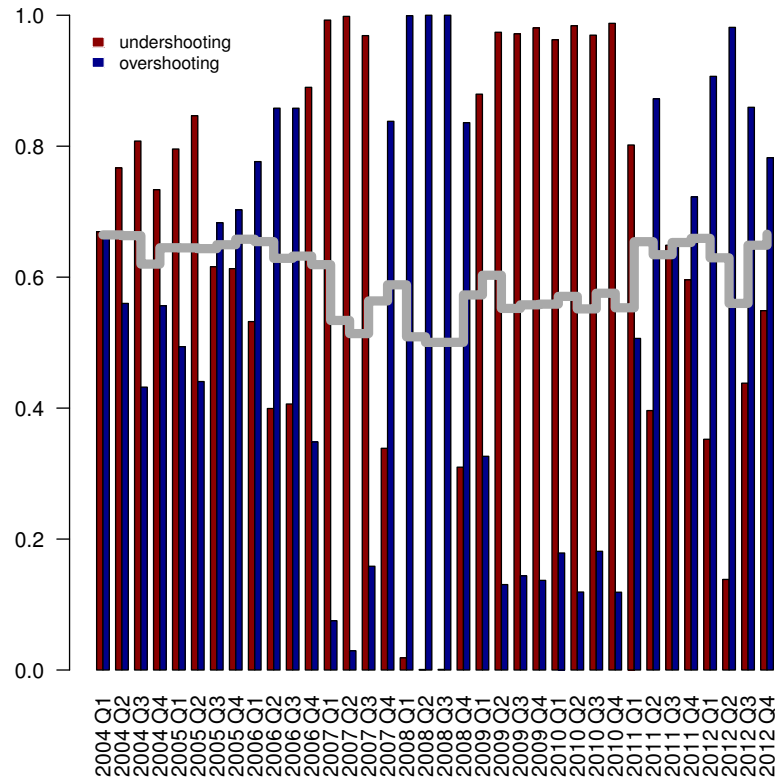


Figure 2.9: Quarterly Herding Test Statistic - Jan 2004 to Dec 2012 (5% confidence interval)

change, be it perceived or expected, of let's say 1.7 % per annum (the mean of inflation rate in the last twenty years in France) differently on a discrete scale with five categories than a respondent with a higher income. Separating individuals into groups by clustering methods as the self-organizing Kohonen map would thus lead to a result in which inflation expectations strongly relate to personal experiences and information, appearing as anti-herding in the results above. This was however controlled for by, first, including the sociodemographic information into the fixed effects to distill the cohort/period-level perceptions and expectations, second, in contrast to other works using pseudo panelization, the data was not aggregated on a cohort level. This means the cohort/period-level expectation and perception estimates are based on the sociodemographic variation within each cohort. The frequently cited notion of heterogenous expectations can however not be rejected.

A caveat for the article at hand and the results presented above lies in the data

however. Bernardt et al. (2006) have, as pointed out above, designed the here applied non-parametric test for herding to test the forecasting behavior of professional analysts. This kind of data has the following advantages: first it has a real panel structure over several years, second the exact point of time is known when each analyst published his/her forecast, thus the sequence of forecasts is known. This is unfortunately not the case in the French household survey data where only the month in which the survey took place is known. Therefore a compromise had to be found, namely to apply the test statistic quarterly, using the mean of all prior forecasts within this month as the consensus and comparing it with the cohort-level expectations and the target inflation rate from one year ahead. This implies that a possible adjustment to a consensus, if it takes place, could only be measured once a month and thus three times a quarter. One cannot completely exclude the possibility of different results if this information is available. To further investigate expectation formation with regard to inflation in the context of group or herd behavior, and therefore the timing of expectation formation, it would be desirable to include this information into the data sets of household surveys within the harmonized European household/consumer survey program or to start recording/publishing this information when interviews are conducted.

Given the results outlined above, it would be very interesting to verify the findings especially with regard to the phase around the beginning of the financial crisis with other, possibly quantitative, survey questions. The University of Michigan Consumer survey used in Chapters 3 and 4 for example contains a question which asks for quantitative inflation expectations. Considering the interpretation from above, namely that the anti-herding behavior with regard to inflation expectations found in this study might be due to agents' heterogeneous consumption behavior, it would however be probably more interesting to repeat the herding test for variables which are more general, like gdp growth or unemployment. With quantitative data like this it would be for example possible to apply, knowing the distributional properties of the expectation values, simulation techniques to gain better understanding of what drives consumers expectation formation process.

## Acknowledgements

I would like to thank François Gardes and Christophe Starzec for their helpful comments, as well as my discussants at the conference of the Société canadienne de science économique 2013 (Quebec Ville, Canada) and at the Journées de Microéconomie Appliquée 2013 (Nice, France).



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## 2.B Variance of the Test statistics

The following sections contain the procedure to compute the variance along Bernardt et al. (2006). If the realized variable  $\pi_{t+1}$  in period  $t + 1$  in relation to the agents  $j$  posterior (the median of  $j$ 's posterior distribution over the realized variable) is given by,

$$\pi_{t+1} = \hat{\pi}_{j,t,t+1}^e + \epsilon_{j,t+1} \quad (2.29)$$

where  $\epsilon_{j,t+1} \sim G(\cdot)$  and  $\epsilon_{t+1}$  is independent and identically distributed over the period of measurement for the forecasted variable and  $G(0) \equiv 0.5$  and if the forecast is unbiased, it holds that  $\pi_{j,t,t+1}^e = \hat{\pi}_{j,t,t+1}^e$ , and the overshooting/undershooting indicator is distributed binomially as,

$$\sum_t \delta_t^+ \sim \mathcal{B}(\sum_t \gamma_t^+, G(0)) \quad \sum_t \delta_t^- \sim \mathcal{B}(\sum_t \gamma_t^-, 1 - G(0)) \quad (2.30)$$

This means the test statistic  $S(z_t^-, z_t^+)$  is asymptotically normal distributed as

$$S \sim \mathcal{N}(0.5, \frac{1}{16} \left[ \frac{1}{\sum_t \gamma_t^+} + \frac{1}{\sum_t \gamma_t^-} \right]) \quad (2.31)$$

since the mean of  $S(z_t^-, z_t^+)$  is

$$\frac{1}{2} \left[ P(\pi_{j,t,t+1}^e > \pi_{t+1}) + P(\pi_{j,t,t+1}^e < \pi_{t+1}) \right] = 0.5[(1 - G(0)) + G(0)] = 0.5 \quad (2.32)$$

and Variance corresponds to

$$\begin{aligned} Var(S(z_t^-, z_t^+)) &= Var\left(\frac{\sum_t \delta_t^+}{\sum_t \gamma_t^+}\right) + Var\left(\frac{\sum_t \delta_t^-}{\sum_t \gamma_t^-}\right) \\ &= \frac{1}{4(\sum_t \gamma_t^+)^2} Var(\sum_t \delta_t^+) + \frac{1}{4(\sum_t \gamma_t^-)^2} Var(\sum_t \delta_t^-) \\ &= \frac{1}{4(\sum_t \gamma_t^+)^2} G(0)(1 - G(0))(\sum_t \gamma_t^+) + \frac{1}{4(\sum_t \gamma_t^-)^2} G(0)(1 - G(0))(\sum_t \gamma_t^-) \\ &= \frac{G(0)(1 - G(0))}{4} \left[ \frac{1}{\sum_t \gamma_t^+} + \frac{1}{\sum_t \gamma_t^-} \right] \end{aligned} \quad (2.33)$$

Accordingly in the case of a commonly unforecasted shock to the forecasted variable,  $\omega_{t+1}$ <sup>12</sup>,  $\sum_t \delta_t^+ \sim \mathcal{B}(\sum_t \gamma_t^+, G(-\omega_t))$  and  $\sum_t \delta_t^- \sim \mathcal{B}(\sum_t \gamma_t^-, 1 - G(-\omega))$ , which however leaves the mean, given the forecast is unbiased  $\pi_{j,t,t+1}^e = \hat{\pi}_{j,t,t+1}^e$  of  $S(\cdot)$ ,

$$\begin{aligned} &\frac{1}{2} \left[ P(\pi_{j,t,t+1}^e > \pi_{t+1}) + P(\pi_{j,t,t+1}^e < \pi_{t+1}) \right] \\ &= \frac{1}{2} \left[ P(\hat{\pi}_{j,t,t+1}^e > \hat{\pi}_{j,t,t+1}^e + \omega_{t+1} + \epsilon_{j,t+1}) + P(\hat{\pi}_{j,t,t+1}^e < \hat{\pi}_{j,t,t+1}^e + \omega_{t+1} + \epsilon_{j,t+1}) \right] \end{aligned}$$

<sup>12</sup>thus with commonly unforecasted shock  $\omega_{t+1}$ ,  $\pi_{t+1} = \hat{\pi}_{j,t,t+1}^e + \omega_{t+1} + \epsilon_{j,t+1}$

$$\begin{aligned}
&= \frac{1}{2} [P(\epsilon_{j,t+1} < -\omega_{t+1}) + P(\epsilon_{j,t+1} > -\omega_{t+1})] \\
&0.5[G(-\omega_{t+1}) + (1 - G(-\omega_{t+1}))] = 0.5
\end{aligned}$$

unaltered. The variance on the other hand is,

$$\frac{G(-\omega_{t+1})(1 - G(-\omega_{t+1}))}{4} \left[ \frac{1}{\sum_t \gamma_t^+} + \frac{1}{\sum_t \gamma_t^-} \right] \leq \frac{1}{16} \left[ \frac{1}{\sum_t \gamma_t^+} + \frac{1}{\sum_t \gamma_t^-} \right]$$

Therefore the variance is at a maximum if  $\omega = 0$  as  $G(-\omega_{t+1})(1 - G(-\omega_{t+1})) \leq G(0)(1 - G(0)) = \frac{1}{2}$ , which means that cross-sectional correlation reduces the variance of the test statistic. The same argumentation can also be used to show that the test statistics is robust to the other two problems addressed above: a bias caused by optimism/pessimism, as well as measurement errors (Bernardt et al., 2006, pp. 664).



## 2.C Robustness

The herding test of Bernardt et al. (2006) is suited for the application to inflation expectations insofar as it is robust to systematic biases of respondents in their perceptions/expectations.

**Commonly unforecasted shocks** With regard to inflation this could for example be a generally unanticipated rise of commodity (oil) prices due to the outbreak of an armed conflict which would eventually lead to a shortage of supply. In this case a general shortfall of forecasts with regard to the realized inflation, leading to the estimation of the conditional probability  $P(\pi_{t+1} < \pi_{t,t+1}^e | \bar{\pi}_{t,t+1}^e < \pi_{t,t+1}^e, \pi_{t,t+1}^e \neq \pi_{t+1}) > \frac{1}{2}$ , and thus to the wrong conclusion that a herding-like bias was a reason for that. Consider a commonly unforecasted shock to the forecasted variable (here inflation)  $\omega_{t+1} > 0$ , be  $\epsilon_{t+1}$  the idiosyncratic shock to inflation and  $G$  its cumulative distribution function. Despite a forecast is unbiased,  $\hat{\pi}_{t,t+1}^e = \pi_{t,t+1}^e$ , this would lead unconditionally to the conclusion of herding,  $P(\pi_{t+1} < \pi_{t,t+1}^e | \bar{\pi}_{t,t+1}^e < \pi_{t,t+1}^e, \pi_{t,t+1}^e \neq \pi_{t+1}) < \frac{1}{2}$ , since  $P(\hat{\pi}_{t,t+1}^e + \omega_{t+1} + \epsilon_{t+1} < \pi_{t,t+1}^e) = P(\hat{\pi}_{t,t+1}^e + \omega_{t+1} + \epsilon_{t+1} < \hat{\pi}_{t,t+1}^e) = P(\epsilon_{t+1} < -\omega_{t+1}) = G(-\omega_{t+1}) < \frac{1}{2}$ . This is also true the other way around: with  $\hat{\pi}_{t,t+1}^e = \pi_{t,t+1}^e$ ,  $P(\hat{\pi}_{t,t+1}^e + \omega_{t+1} + \epsilon_{t+1} > \pi_{t,t+1}^e) = P(\hat{\pi}_{t,t+1}^e + \omega_{t+1} + \epsilon_{t+1} > \hat{\pi}_{t,t+1}^e) = P(\epsilon_{t+1} > -\omega_{t+1}) = 1 - G(-\omega_{t+1}) > \frac{1}{2}$ , which implies  $P(\pi_{t+1} < \pi_{t,t+1}^e | \bar{\pi}_{t,t+1}^e < \pi_{t,t+1}^e, \pi_{t,t+1}^e \neq \pi_{t+1}) > \frac{1}{2}$ . A simple and effective solution, as pointed out by Bernardt et al. (2006), could be to use the average, as  $\omega_t$  can be assumed to have offsetting effects. Under the assumption of unbiasedness  $\hat{\pi}_{t,t+1}^e = \pi_{t,t+1}^e$ , the test statistic, despite of the commonly unforecasted shock, would still yield 0.5, as  $0.5[G(-\omega_{t+1}) + (1 - G(-\omega_{t+1}))] = \frac{1}{2}$ .

**Optimism/Pessimism** The same would be true if a certain degree of optimism or pessimism distorts the forecasts. The phenomenon discussed by Bernardt et al. (2006) is that forecasts further in the past tend to be more optimistic, while forecasts nearer to the disclosure of the realized value, as more information becomes available, tend to be more pessimistic. Such an effect can be modeled by introducing a bias  $\alpha_t$  which changes over time. For example one can assume that  $t$  days before the disclosure of the realized value an agent forecasts the  $\alpha$  percentile of the forecasted value. The result could be a false conclusion with regard to the presence of herding as in the case of commonly unforecasted earning shocks. Analogously to the latter case, this problem can also be addressed by taking averages, since  $\frac{1}{2}P(\pi_{t+1} < \pi_{t,t+1}^e | \bar{\pi}_{t,t+1}^e < \pi_{t+1}) + \frac{1}{2}P(\pi_{t+1} > \pi_{t,t+1}^e | \bar{\pi}_{t,t+1}^e > \pi_{t+1}) = \frac{1}{2}[\alpha_t + (1 - \alpha_t)] = \frac{1}{2}$  rendering the conclusion if herding was present or not, unaltered.

**Measurement errors** The problem of measurement errors might become relevant, as the value targeted by the agent in his forecast and its measurement differ (a different perception of price changes due to different consumption behavior). As mentioned above an individual might base its estimation of price changes on a mix of products, which is different compared to the basket of goods used by the statistical office in the calculation

of the official rate of inflation for a certain period of time: The agent targets  $\pi_{t+1}$  with  $\pi_{t,t+1}^e = \hat{\pi}_{t,t+1}^e$  while the realized value  $\pi_{t+1}$  is measured as  $\pi_{t+1} + \lambda_{t+1}$ . Similarly, as  $\frac{1}{2}P(\pi_{t+1} < \pi_{t,t+1}^e | \bar{\pi}_{t,t+1}^e < \pi_{t,t+1}^e) + \frac{1}{2}P(\pi_{t+1} > \pi_{t,t+1}^e | \bar{\pi}_{t,t+1}^e > \pi_{t,t+1}^e) = \frac{1}{2}[G(\lambda_{t+1}) + (1 - G(\lambda_{t+1}))] = \frac{1}{2}$ , this effect can be offset by using the average.

All the above discussed issues are also controlled for in the modification of the non-parametric test used in this article, as computing the conditional probabilities directly from the estimated posterior distributions is equivalent to the averaging applied in the original test proposed by Bernardt et al. (2006).



## 2.D Variables - coding

variable	type	question	code	description
age	numeric	age	-	-
childs	numeric	number of children	-	-
citysize	ordered var.		0	rural
			1	less 5000 inhabitants
			2	between 5,000 and 9,999
			3	between 10,000 and 19,999
			4	between 20,000 and 49,999
			5	between 50,000 and 99,999
			6	between 100,000 and 199,999
			7	between 200,000 and 1,999,999
			8	Paris metropolitan region
educ	ordered var.	education	1	primary education or less
			2	secondary education
			3	post secondary education
			4	tertiary education
econ_per	ordered var.	The general economic situation in France in the last 12 months	1	significantly worsened
			2	slightly worsened
			3	stayed the same
			4	improved a bit
			5	significantly improved
econ_exp	ordered var.	The general economic situation in France in the next 12 months	1	will worsen significantly
			2	will slightly worsen
			3	will stay the same
			4	will improve a bit
			5	will improve significantly

finan	categorical var.	What describes best the financial situation of your household	1 2 3 4 5	enough income to save a sufficient amount enough income to save a bit sufficient income to cover expenses have to use reserves to cover expenses coverage of expenses only possible with borrowing
fracwork	numeric	fraction of persons in the household with a job	-	-
price_per	ordered var.	Do you thin that prices in the last 12 months have	1 2 3 4	decreased stagnated increased moderately increased strongly
price_exp		In comparison with the last 12 months how do you think the evolution of prices will be in the next 12 months	1 2 3 4 5	prices will go down prices will stay the same prices will increase with a smaller rate prices will increase with the same rate prices will increase with a faster rate
region	categorical var.	region of residence	11 21 22 23 24 25 26 31	Île-de-France Champagne-Ardenne Picardie Haute-Normandie Centre Basse-Normandie Bourgogne Nord-Pas-de-Calais



			41	Lorraine
			42	Alsace
			43	Franche-Comté
			52	Pays de Loire
			53	Bretagne
			54	Poitou-Charentes
			72	Aquitaine
			73	Midi-Pyrénées
			74	Limousin
			82	Rhône-Alpes
			83	Auvergne
			91	Languedoc-Roussillon
			93	Provence-Alpes-Côte d'Azur
			94	Corse
revquart	ordered var.	income quartile	1	1st quartile
			2	2nd quartile
			3	3rd quartile
			4	4th quartiles
sex	categorical var.		1	male
			2	female
workregime	categorical var.		1	full time
			2	part time
			0	don't know/no answer
			or 9	
spouse	categorical var.		1	yes
			2	no
occupation	categorical var.		1	yes
			2	no, unemployed
			3	no, retired
			4	no, inactive
birthyr	numeric	birthyear	-	-



## 2.E Inflation perceptions and expectations for each cohort

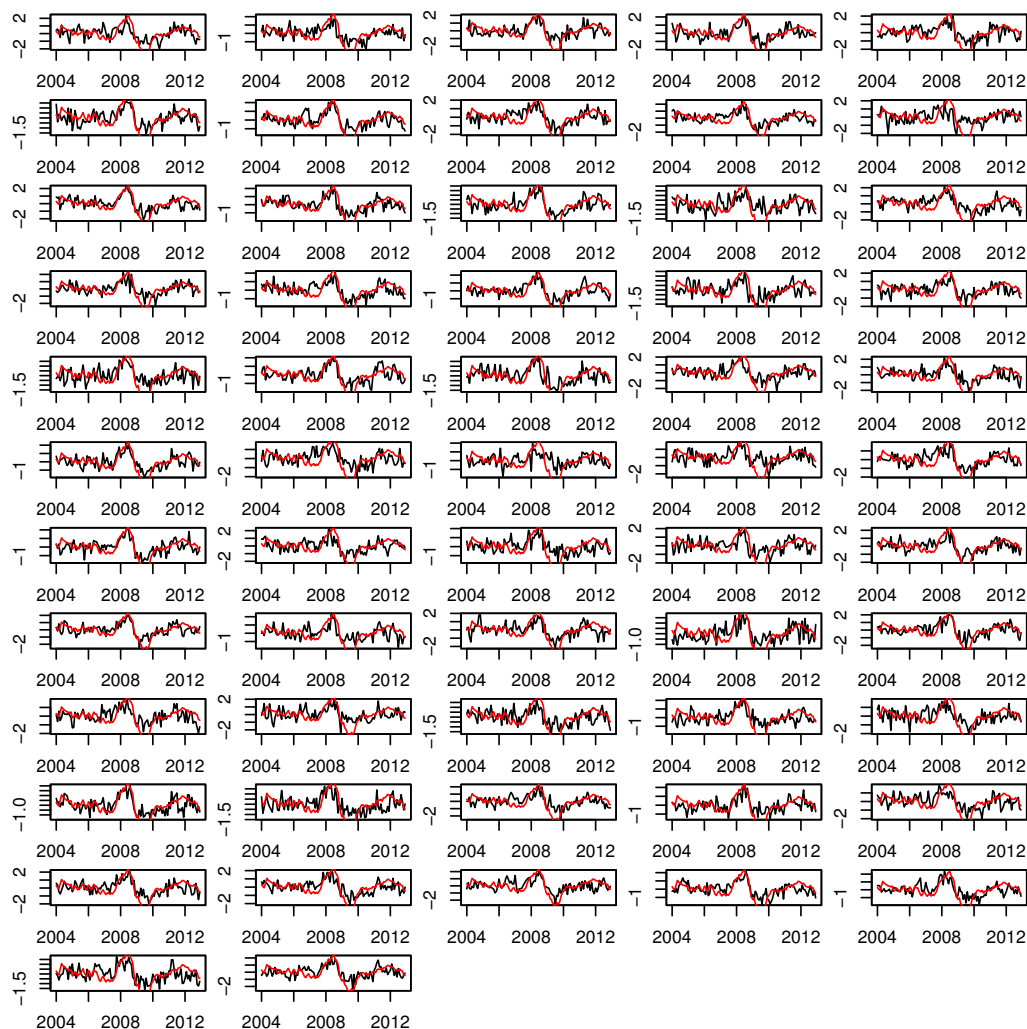


Figure 2.10: Perceived inflation vs. actual inflation for each cohort

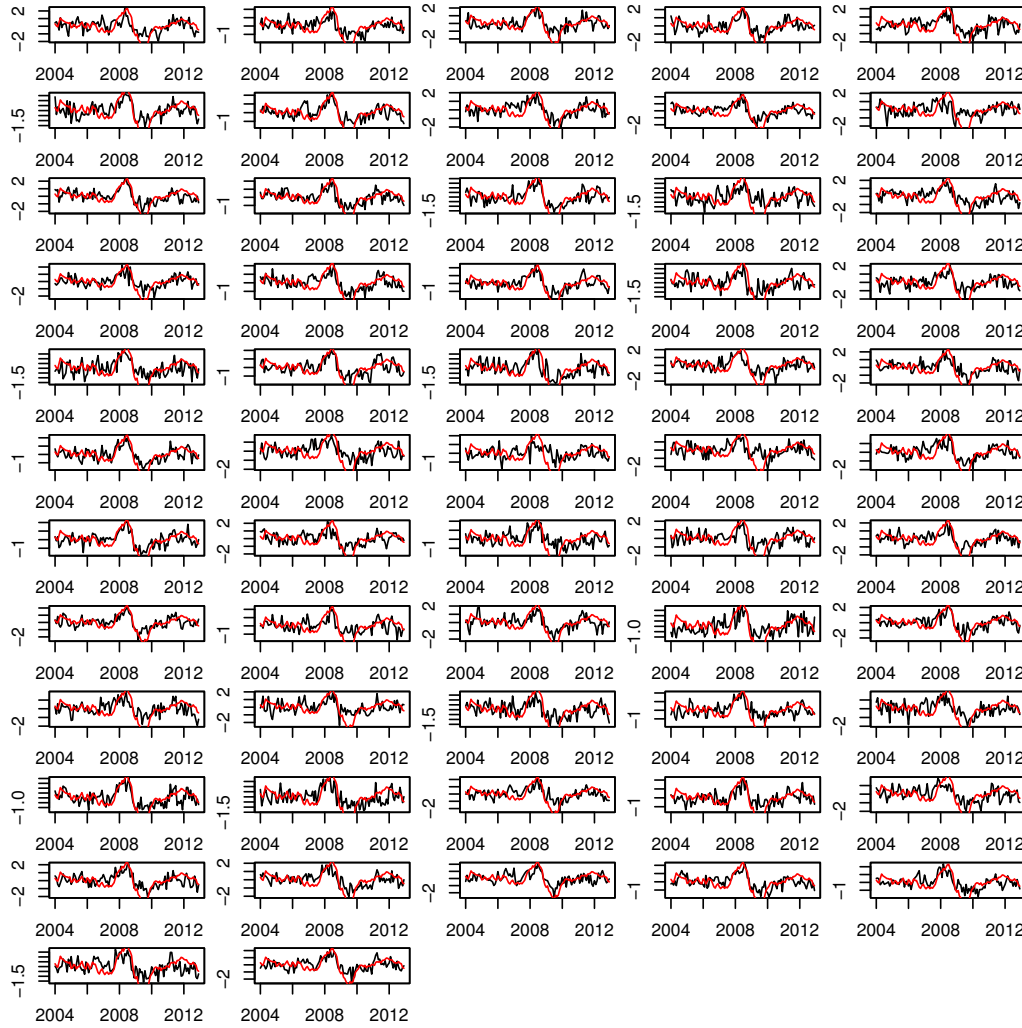


Figure 2.11: Expected inflation vs. actual inflation for each cohort

## Chapter 3

# Decomposing the rationality bias in Expectations

### 3.1 Introduction

#### 3.1.1 The Data Set: University of Michigan Consumer Survey

The University of Michigan consumer survey (MCS) is a household survey conducted by the Survey Research Center of the University of Michigan since 1966. Each month at least 500 representative households from the United States excluding Hawaii and Alaska are selected and surveyed with regard to their perceptions and expectations of their personal economic well-being as well as general economic variables as the inflation rate, business conditions, unemployment rate, etc. Additionally to that the survey collects a wide variety of sociodemographic information as for example the household size, the marital status, the household income, the age, the education and the race of the respondent. Table 3.1 gives an overview of the sociodemographic features of the survey respondents within the data set at the time the article at hand was written. The data set of the Michigan consumers survey available at the time this article was written comprises around 224,000 records collected between July 1980 and October 2014. An important and for research purposes very interesting feature of the Michigan consumer survey is its panel structure. Although it is limited to only about 40% of the data set or 89,000 respondents it allows the researcher a unique insight in the expectation formation process. In the specific context of the present article this feature of the survey data set permits to compare the expectations of respondents with regard to specific variables and their perception thereof when they are surveyed again one year later.

#### 3.1.2 Research question and methodology

The paper at hand ties up to the wide stream of empirical research on the rational expectations hypothesis. While the biggest part of the existing research focuses on the hypothesis of rational expectations itself, some finding evidence for it like Thomas (1999) and Ang et al. (2007) others rejecting it as for example Mehra (2002), Roberts



sex	race	education	n	income		age	
				mean	sd	mean	sd
male	white	no highschool	8469	23426	25055	54	19
		highschool	45461	42941	39804	45	17
		college	33588	72136	69737	46	15
	afro-american	no highschool	1270	17397	16968	53	18
		highschool	4274	35022	29083	40	15
		college	1839	59223	51972	43	14
	hispanic	no highschool	1043	23593	23742	43	17
		highschool	2443	41167	34824	37	14
		college	971	68648	64950	40	13
	other	no highschool	210	22332	26182	47	19
		highschool	1083	42009	40626	38	15
		college	1524	78196	74897	42	13
female	white	no highschool	10838	16299	18221	58	19
		highschool	59385	36191	34955	48	18
		college	31764	64120	60987	45	16
	afro-american	no highschool	2261	11521	12327	55	18
		highschool	6835	26511	23453	41	16
		college	2883	49061	40671	42	14
	hispanic	no highschool	1597	18634	19417	44	16
		highschool	3090	35376	33411	38	14
		college	1173	65549	61744	40	12
	other	no highschool	280	20692	22928	51	17
		highschool	1166	36225	38248	40	16
		college	1393	79189	73228	41	12
All		224840	45814	49725	46	17	

Table 3.1: University of Michigan Consumer Survey: Descriptive Statistics

(1997) or Baghestani (2009), this paper tackles this question from a somewhat different perspective. Exploiting the panel structure of the Michigan consumer survey, the survey population is split into two groups:

1. Respondents whose expectations and perceptions when asked one year later with regard to a certain variable correspond to each other. In other words these respondents would fulfill the basic notion of expectational rationality.
2. The rest of the survey population for which this is not the case, as they are either over- or understating the development of a certain variable when compared to their perceptions of the same variable when asked again twelve months after the first interview. One could thus say that they were either too optimistic or pessimistic. Specifically this paper concentrates on the following questions or variables:<sup>1</sup>

**General economic condition:** The qualitative variables *BEXP* and *BAGO* in the Michigan consumer survey capture the respondents expectations and perceptions with regard to the general economic situation:

<sup>1</sup>In all cases non-responses were excluded.

*BEXP:* “[...] *do you expect that in the country as a whole business conditions will be better, or worse than they are at present, or just about the same?*”

1. Worse a year from now
2. About the same
3. Better a year from now

*BAGO:* “*Would you say that at the present time business conditions are better or worse than they were a year ago?*”

1. Worse now
2. About the same
3. Better now

**Personal Finances:** With the variables *PEXP* and *PAGO* the survey evaluates the expectations and perceptions of respondents with regard to their personal financial situation:

*PEXP:* “*Now looking ahead – do you think that a year from now you will be better off financially, or worse off, or just about the same as now?*”

1. Will be worse off
2. Same
3. Will be better off

*PAGO:* “[...] *Would you say that you are better off or worse off financially than you were a year ago?*”

1. Worse now
2. Same
3. Better now

**Consumer Prices:** The evolution of consumer prices are covered by two variables in the survey, which are however only forward looking. *PX1Q1*, in the remainder of the text coded as *CPEXP\_CAT*, is qualitative, while *PX1Q2* to which I will further refer as *CPEXP\_PER* asks for a specific quantitative value:



*CPEXP\_CAT*: “[...]During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now?”

1. Go down
2. Same
3. Go up (at same rate or more)

In the Michigan consumer survey *CPEXP\_CAT* is coded in four levels, this means it differentiates between “Go up (at the same rate)” and “Go up”. For reasons of comparability these two categories however had that to be merged in the context of this work.

*CPEXP\_PER*: “By about what percent do you expect prices to go (up/down) on the average, during the next 12 months?”

Both of the questions with regard to the consumer prices are unfortunately missing a backward looking (perception) question. This problem could be circumvented in the case of the quantitative question by using the actual inflation rate in the respective period. This is however not ideal. The perception of price evolution depends on the individual consumption behavior and is thus highly heterogeneous<sup>2</sup>. To take this into account I am using a method suggested by Lahiri and Zhao (2015) to quantify qualitative survey expectations. The approach using an hierarchical ordered probit model allows to estimate time varying as well as cross-section specific threshold values which permit to convert the true inflation rate into a cross-section specific ordered variable with three categories. This will in turn serve as the perception variable *CPPER\_CAT* which can be compared to the qualitative expectation variable *CPEXP\_CAT*. Thereby one can evaluate the expectational rationality/optimism/pessimism of an individual with regard to inflation as if both a forward looking (expectation) as well a backward looking (perception) variable would be available. The same method will be applied to expectations concerning unemployment where again only a forward looking question is available in the Michigan consumer survey:

**Unemployment:** The qualitative variable *UNEMP*, in the remainder of the article referred to as *UEEXP*, captures the respondents expectations with regard to the evolution of unemployment in the 12 months ahead.

*UEEXP*: “How about people out of work during the coming 12 months – do you think that there will be more unemployment than now, about the same, or less?”

1. Less unemployment
2. About the same

---

<sup>2</sup>This is for example the result of Chapter 2



### 3. More unemployment

As mentioned above this variable also has to be quantified in order to obtain individual specific qualitative perception information (*UEPER*). Once all the expectation as well as a perception data is available, a non-linear extension of the detailed Oaxaca-Blinder decomposition is used to investigate the differences between “rational” respondents on the one hand and optimistic/pessimistic respondents on the other hand. In the case of the quantitative price expectation data in the form of the variable *CPEXP\_PER* the standard linear version of the Oaxaca-Blinder decomposition is used as a control.

Section 3.2 is devoted to a detailed outline of the decomposition method. In Section 3.3 the HOPIT-method to quantify qualitative survey expectations is presented. It will further on comprise a more detailed description of how these method is used to obtain cross-section specific qualitative perception information via the estimated thresholds. Section 3.3.4 finally discusses the grouping of the survey population into rational and optimistic/pessimistic individuals respectively and Section 3.4 presents the results of the decomposition procedure.

## 3.2 Decomposition Methodology

### 3.2.1 Basic two-fold decomposition

The decomposition method used in this paper is an extension of the original Blinder-Oaxaca approach (Blinder, 1973; Oaxaca, 1973). Let  $N$  and  $K$  be the numbers of observations and parameters respectively, then  $Y$  is the  $N \times 1$  vector representing the explained variable,  $X$  is the  $N \times K$  data matrix and  $\beta$  is the  $K \times 1$  parameter vector. It is assumed that a function  $F(\cdot)$ , maps a linear combination of  $X$  ( $X\beta$ ) to  $Y$  (Powers et al., 2011, p. 558):

$$Y = F(X\beta) \quad (3.1)$$

The properties of  $F(\cdot)$  depend on the respective estimation technique which in the context of this paper are *ordinary least squares* and *ordered probit* and will be discussed later on. The goal in any case is to decompose the mean difference between two groups  $A$  and  $B$  ( $\bar{Y}_A - \bar{Y}_B$ ) into a data related effect ( $E$ ) on the one hand and a coefficient related effect ( $C$ ) on the other hand:

$$\hat{D} = \bar{Y}_A - \bar{Y}_B = \overline{F(X_A\beta_A)} - \overline{F(X_B\beta_B)} \quad (3.2)$$

$$= \underbrace{\left[ \overline{F(X_A\beta_A)} - \overline{F(X_B\beta_A)} \right]}_E + \underbrace{\left[ \overline{F(X_B\beta_A)} - \overline{F(X_B\beta_B)} \right]}_C \quad (3.3)$$

The notation  $\bar{Y}_B = \overline{F(X_A\beta_A)}$  and  $\bar{Y}_B = \overline{F(X_B\beta_B)}$  refers to the mean outcomes of groups  $A$  and  $B$  respectively. Equivalently  $\overline{F(X_A\beta_B)}$  corresponds to the mean outcome computed using data from group  $A$  with coefficients from group  $B$ . The intuition behind the Oaxaca-Blinder decomposition is the following: While for component  $E$  group specific

subsets of the data set are used but the same coefficients, in component  $C$  the difference is computed using the same data subset but group specific coefficients. Component  $E$  thus corresponds to measuring the impact of the data on the difference in outcomes assuming that the relationship (the coefficients) between data and the outcome is invariant with respect to the different groups. For the  $C$  component this is other way around: Using the same subset of the data but group specific coefficients allows to isolate the difference in outcomes which are due to a difference in coefficients and thus the way how the data relates to the outcomes. The idea behind this sort of decomposition was initially to investigate to which extent the difference between wages of men and women is related to discrimination.  $E$  therefore comprises the part of the wage gap which is explainable by the data as for example by differences of education, work experience etc., while  $C$  captures effects which are not explainable by the data and given the model is well calibrated might be due to discrimination. If the estimation for example only contains a one explanatory variable referring to the years of schooling and  $A$  corresponds to the male and  $B$  to the female subgroup a positive  $C$  component indicates that females generate a lower marginal gain in terms of salary for one additional year of schooling than their male counterparts. In other words women are rewarded to a lesser extent for more education. This means discrimination can be assumed.

A decomposition of this sort is of course sensitive to the choice of the reference group, this means to stick to the above mentioned example of the wage difference between men and women on the definition of the wage which one regards as non-discriminatory. The non-discriminatory wage is not necessarily the higher one. One could for example assume that one part of the wage difference is due to the positive discrimination of one group, which means that the true non-discriminatory wage might lie between the wage rate of group A and group B. In equation (3.3) the reference group is assumed to be group A. This assumption can be lifted by using a different non-discriminatory vector of coefficients  $\beta_R$  (Jann, 2008, pp. 3).

$$\hat{D} = \left[ \overline{F(X_A \beta_R)} - \overline{F(X_B \beta_R)} \right] + \left[ \overline{F(X_B \beta_R)} - \overline{F(X_B \beta_B)} \right] \quad (3.4)$$

In the literature different suggestions for  $\beta_R$  can be found. Reimers (1983) suggests to use the average between the coefficient vectors of group A and B,  $\beta_R = 1/2\beta_A + 1/2\beta_B$ . Cotton (1988) proposes to weight the group specific coefficients by their respective sample sizes,  $\beta_R = N_A/(N_A + N_B) * \beta_A + N_B/(N_A + N_B) * \beta_B$ . A third method to approximate  $\beta_R$  stems from Neumark (1988) who recommends to use the coefficient vector from a pooled regression with group A and B.

### 3.2.2 Detailed Decomposition

Expression (3.4) can be further decomposed to the contribution of each parameter, thus the weight of each parameter within both components, namely  $W_{\Delta X}^i$  as far as the endowment effects (E) are concerned and  $W_{\Delta \beta}^i$  for the coefficient effects (C):

$$\hat{D} = \sum_{i=1}^K W_{\Delta X}^i \left[ \overline{F(X_A \beta_R)} - \overline{F(X_B \beta_R)} \right] + \sum_{i=1}^K W_{\Delta \beta}^i \left[ \overline{F(X_B \beta_R)} - \overline{F(X_B \beta_B)} \right] \quad (3.5)$$



Following Yun (2004) mean characteristics are used in order to rewrite (3.4):

$$\hat{D} = \left[ F(\bar{X}_A \beta_R) - F(\bar{X}_B \beta_R) \right] + \left[ F(\bar{X}_B \beta_R) - F(\bar{X}_B \beta_B) \right] + R_M \quad (3.6)$$

where

$$R_M = \left[ \overline{F(X_A \beta_R)} - \overline{F(X_B \beta_R)} \right] + \left[ \overline{F(X_B \beta_R)} - \overline{F(X_B \beta_B)} \right] \\ - \left[ F(\bar{X}_A \beta_R) - F(\bar{X}_B \beta_R) \right] - \left[ F(\bar{X}_B \beta_R) - F(\bar{X}_B \beta_B) \right]$$

Then the  $C$  and the  $E$  components are linearized around  $X_A \beta_R$  and  $X_A \beta_B$  by a first order Taylor expansions respectively.

$$\hat{D} = \frac{\delta F(\bar{X}_A \beta_R)}{\delta(\bar{X}_A \beta_R)} (\bar{X}_A \beta_R - \bar{X}_B \beta_R) + \frac{\delta F(\bar{X}_B \beta_B)}{\delta(\bar{X}_B \beta_B)} (\bar{X}_B \beta_R - \bar{X}_B \beta_B) + R_M + R_T \\ = (\bar{X}_A - \bar{X}_B) \beta_R f(\bar{X}_A \beta_R) + \bar{X}_B (\beta_R - \beta_B) f(\bar{X}_B \beta_B) + R_M + R_T \quad (3.7)$$

where

$$R_T = \left[ F(\bar{X}_A \beta_R) - F(\bar{X}_B \beta_R) \right] + \left[ F(\bar{X}_B \beta_R) - F(\bar{X}_B \beta_B) \right] \\ - (\bar{X}_A - \bar{X}_B) \beta_R f(\bar{X}_A \beta_R) + \bar{X}_B (\beta_R - \beta_B) f(\bar{X}_B \beta_B)$$

Using (3.7) one can express the weights  $W_{\Delta X}^i$  and  $W_{\Delta \beta}^i$  respectively.

$$W_{\Delta X}^i = \frac{(X_A^i - X_B^i) \beta_R^i f(\bar{X}_A \beta_R)}{(X_A - X_B) \beta_R f(\bar{X}_A \beta_R)} = \frac{(X_A^i - X_B^i) \beta_R^i}{(X_A - X_B) \beta_R} \quad (3.8)$$

$$W_{\Delta \beta}^i = \frac{\bar{X}_B^i (\beta_R^i - \beta_B^i) f(\bar{X}_B \beta_B)}{\bar{X}_B (\beta_R - \beta_B) f(\bar{X}_B \beta_B)} = \frac{\bar{X}_B^i (\beta_R^i - \beta_B^i)}{\bar{X}_B (\beta_R - \beta_B)} \quad (3.9)$$

The weights (3.8) and (3.9) obviously have to sum up to one:  $\sum_{i=1}^K W_{\Delta X}^i = 1$  and  $\sum_{i=1}^K W_{\Delta \beta}^i = 1$

### 3.2.3 Extending the decomposition method to non-linear models

As far as linear models are concerned the mapping  $F(\cdot)$  from  $X$  to  $Y$  is simply  $X\beta$  and thus  $\bar{Y} = \overline{F(X\beta)} = \bar{X}\beta$ . In an ordered probit/logit and thus non-linear framework which shall be used complementary in the article at hand this is not the case. Here the dependent variable is censored and thus only available in the form of a discrete variable with finite, ordered response categories.

$$Y = \begin{cases} 1 & \text{if } Y^* \leq \mu_1, \\ 2 & \text{if } \mu_1 < Y^* \leq \mu_2, \\ 3 & \text{if } \mu_3 < Y^* \leq \mu_4 \\ \vdots & \\ J-1 & \text{if } \mu_{J-1} < Y^* \leq \mu_{J-2} \\ J & \text{if } \mu_{J-1} < Y^*. \end{cases}$$

The latent variable  $Y^*$  is a continuous though unobserved version of the ordinal variable  $Y$ . Threshold points  $\mu_i$  with  $i = 1, \dots, J - 1$  which are estimated within the maximum likelihood estimation of the ordered probit model define the intervals of the latent variable  $Y^*$  which correspond to the  $J$  ordered categories. Making use of the ordered probit assumption that  $Y^* = X\beta + \epsilon$  with  $\epsilon \sim \mathcal{N}(0, 1)$  once can write down the probability for each category:

$$\begin{aligned}
 P(Y = 1|X) &= P(Y^* \leq \mu_1|X) = P(X\beta + \epsilon \leq \mu_1|X) = F(\mu_1 - X\beta|X) \\
 P(Y = 2|X) &= P(\mu_1 < Y^* \leq \mu_2|X) = F(\mu_2 - X\beta|X) - F(\mu_1 - X\beta|X) \\
 P(Y = 3|X) &= P(\mu_2 < Y^* \leq \mu_3|X) = F(\mu_3 - X\beta|X) - F(\mu_2 - X\beta|X) \\
 &\vdots \\
 P(Y = J|X) &= P(Y^* > \mu_J) = 1 - F(\mu_J - X\beta)
 \end{aligned}$$

In the ordered probit case  $F(\cdot)$  corresponds to the cumulative distribution function of the standard normal distribution  $\Phi(\cdot)$ . Using the cumulative logistic distribution function  $\Lambda(\cdot)$  would correspond to an ordered logit model. Based upon this and following Bauer and Sinning (2008) one can write down an equation for the conditional expectations of  $Y$  to which the decomposition techniques outlined in subsection 3.2.1 and 3.2.2 can be applied.

$$\begin{aligned}
 E_{\beta_g}(Y_{ig}|X_{ig}) &= \sum_{j=1}^J j \cdot P(Y_{ig} = j|X_{ig}) \\
 &= 1 \cdot [F(\mu_{1g} - X_{ig}\beta_g)] \\
 &\quad + 2 \cdot [F(\mu_{2g} - X_{ig}\beta_g) - F(\mu_1 - X_{ig}\beta_g)] \\
 &\quad + 3 \cdot [F(\mu_{3g} - X_{ig}\beta_g) - F(\mu_2 - X_{ig}\beta_g)] \\
 &\quad \vdots \\
 &\quad + J \cdot [1 - F(\mu_{Jg} - X_{ig}\beta_g)]
 \end{aligned} \tag{3.10}$$

Here  $g \in \{A, B\}$  again denotes the reference group to which individual  $i$  belongs. Following Bauer and Sinning (2008) one can rewrite equation (3.10) to its sample version:

$$\begin{aligned}
 S(\hat{\beta}_g, \hat{\mu}_{jg}, X_{ig}) &= \frac{1}{N} \sum_{i=1}^N \sum_{j=1}^J j \cdot P(Y_{ig} = j|\hat{\beta}_g, \hat{\mu}_{jg}, X_{ig}) \\
 &= \frac{1}{N} \sum_{i=1}^N \left\{ 1 \cdot [F(\hat{\mu}_{1g} - X_{ig}\hat{\beta}_g)] \right. \\
 &\quad + 2 \cdot [F(\hat{\mu}_{2g} - X_{ig}\hat{\beta}_g) - F(\hat{\mu}_1 - X_{ig}\hat{\beta}_g)] \\
 &\quad + 3 \cdot [F(\hat{\mu}_{3g} - X_{ig}\hat{\beta}_g) - F(\hat{\mu}_2 - X_{ig}\hat{\beta}_g)] \\
 &\quad \vdots
 \end{aligned}$$

$$+ J \cdot [1 - F(\hat{\mu}_{Jg} - X_{ig}\hat{\beta}_g)] \Big\} \quad (3.11)$$

Corresponding to equation (3.4) the decomposition in the context of ordinal models (probit or logit; depending on the choice of the link function) can be written as:

$$\begin{aligned} \hat{D} = & \left[ S(\hat{\beta}_R, \hat{\mu}_{jR}, X_{iA}) - S(\hat{\beta}_R, \hat{\mu}_{jR}, X_{iB}) \right] \\ & + \left[ S(\hat{\beta}_R, \hat{\mu}_{jB}, X_{iB}) - S(\hat{\beta}_B, \hat{\mu}_{jB}, X_{iB}) \right] \end{aligned} \quad (3.12)$$

In contrast to Bauer and Sinning (2008) it is assumed that the choice of  $\mu$  in the two components of the decomposition also plays a central role. The detailed decomposition can be conducted like in the case of the linear model along equations (3.8) and (3.9).

### 3.2.4 Computing the Variance of the decomposition estimates

The variances for the components of the decomposition are computed following Powers et al. (2011) along the delta method introduced by Rao (Rao, 2009, pp. 321).  $E$  can be expressed as the weighted mean of components obtained by the detailed composition outlined in the last but one subsection.

$$E = \sum_{k=1}^K E_k = \sum_{k=1}^K W_{\Delta X_k} \left\{ \overline{F(X_A \beta_R)} - \overline{F(X_B \beta_R)} \right\} \quad (3.13)$$

Taking the partial derivatives of  $E$  with respect to all  $\beta_{R_l}$  results in a gradient  $G_E$  with a dimension of  $1 \times K$  of which  $l^{th}$  element is:

$$\frac{\delta E_k}{\delta \beta_{R_l}} = W_{\Delta X_k} \left\{ \frac{\delta \overline{F(X_A \beta_R)}}{\delta \beta_{R_l}} - \frac{\delta \overline{F(X_B \beta_R)}}{\delta \beta_{R_l}} \right\} + \frac{W_{\Delta X_k}}{\Delta \beta_{R_l}} \left\{ \overline{F(X_A \beta_R)} - \overline{F(X_B \beta_R)} \right\} \quad (3.14)$$

with

$$\frac{W_{\Delta X_k}}{\Delta \beta_{R_l}} = I(k=l) \left\{ \frac{\bar{X}_{A_k} - \bar{X}_{B_k}}{\sum_k \beta_{R_k} (\bar{X}_{A_k} - \bar{X}_{B_k})} \right\} - \frac{\beta_{R_l} (\bar{X}_{A_k} - \bar{X}_{B_k}) (\bar{X}_{A_l} - \bar{X}_{B_l})}{\left\{ \sum_k \beta_{R_k} (\bar{X}_{A_k} - \bar{X}_{B_k}) \right\}^2} \quad (3.15)$$

Here  $I(\cdot)$  is an indicator function and, as far as non-linear models are concerned,  $\frac{F(X_j \beta_j)}{X_{jl}}$  with  $j \in \{A, B, R\}$ . If  $E = (E_1, \dots, E_K)$  is the  $K \times 1$  vector with the elements of the detailed decomposition of  $E$ ,  $G_E$  is the  $K \times K$  gradient matrix and  $\Sigma_{\beta_R}$  is the variance-covariance matrix of the coefficient  $\beta_R$ , then the  $K \times K$  variance-covariance matrix of the detailed decomposition components of  $E$  is:

$$\Sigma_E = G_E \Sigma_{\beta_R} G_E' \quad (3.16)$$

The procedure is similar for the  $C$  component.

$$C = \sum_{k=1}^K C_k = \sum_{k=1}^K W_{\Delta \beta_k} \left\{ \overline{F(X_B \beta_R)} - \overline{F(X_B \beta_B)} \right\} \quad (3.17)$$



Along before one can again derive the gradient vector of the partial derivatives of  $C_k$ . Now however  $C_k$  depends on  $\beta_R$  and  $\beta_B$ . The partial derivatives thus are found by deriving  $C_k$  with respect to  $\beta_R$  and  $\beta_B$  respectively:

$$\frac{\delta C_k}{\delta \beta_{R_l}} = W_{\Delta \beta_k} \overline{f(X_B \beta_R) X_{B_l}} + \frac{W_{\delta \beta_k}}{\delta \beta_{R_l}} \left\{ \overline{F(X_B \beta_R) - F(X_B \beta_B)} \right\} \quad (3.18)$$

$$\frac{\delta C_k}{\delta \beta_{B_l}} = \frac{W_{\delta \beta_k}}{\delta \beta_{B_l}} \left\{ \overline{F(X_B \beta_R) - F(X_B \beta_B)} \right\} - W_{\Delta \beta_k} \overline{f(X_B \beta_B) X_{B_l}} \quad (3.19)$$

with

$$\frac{W_{\delta \beta_k}}{\delta \beta_{R_l}} = I(k=l) \left\{ \frac{\bar{X}_{B_k}}{\sum_k \bar{X}_{B_k} (\beta_{R_k} - \beta_{B_k})} \right\} - \frac{\bar{X}_{B_k} \bar{X}_{B_l} (\beta_{R_k} - \beta_{B_k})}{\{\sum_k \bar{X}_{B_k} (\beta_{R_k} - \beta_{B_k})\}^2} \quad (3.20)$$

$$\frac{W_{\delta \beta_k}}{\delta \beta_{B_l}} = \frac{\bar{X}_{B_k} \bar{X}_{B_l} (\beta_{R_k} - \beta_{B_k})}{\{\sum_k \bar{X}_{B_k} (\beta_{R_k} - \beta_{B_k})\}^2} - I(k=l) \left\{ \frac{\bar{X}_{B_k}}{\sum_k \bar{X}_{B_k} (\beta_{R_k} - \beta_{B_k})} \right\} \quad (3.21)$$

Again  $I(\cdot)$  is an indicator function. If  $C = (C_1, \dots, C_K)$  is the  $K \times 1$  vector with the elements of the detailed decomposition of  $C$ ,  $G_{C_j}$  are the  $K \times K$  gradient matrices for  $j \in \{R, B\}$ ,  $\Sigma_{\beta_R}$  and  $\Sigma_{\beta_B}$  respectively are the variance-covariance matrices of the parameters of the reference group and group B regression, then the  $K \times K$  variance-covariance matrix of the detailed decomposition components of  $C$  is:

$$\Sigma_C = G_{C_A} \Sigma_{\beta_R} G'_{C_A} + G_{C_B} \Sigma_{\beta_B} G'_{C_B} \quad (3.22)$$

The variances of the overall decomposition components  $E$  and  $C$  can be found by summing up the elements of the respective variance-covariance matrices of the detailed decompositions:

$$Var(E) = \mathbf{e}' \Sigma_E \mathbf{e} \quad (3.23)$$

$$Var(C) = \mathbf{e}' \Sigma_C \mathbf{e} \quad (3.24)$$

where  $\{\mathbf{e}_i\}_{i \in I}$  with dimension  $K \times 1$ .

### 3.3 Obtaining cross-section specific perception data by a HOPIT-procedure

#### 3.3.1 The hierarchical ordered probit model

One of the greatest challenges of survey based economic research is to obtain accurate information about the expectations of respondents with regard to various economic variables. A natural approach would of course be to ask individuals for their quantitative expectations directly as this done for example in the Michigan consumer survey by the quantitative question about the price evolution in the next twelve months (variable *CPEXP\_PER*; for more detailed information please refer to Section 3.1). However,

research shows that while individuals have a good feeling for the trend, they often lack an accurate notion of the magnitude. It thus is the standard today in most consumer surveys to ask for qualitative information instead. The question outlined in Section 3.1 (*PEXP/PAGO*, *BEXP/BAGO*, *CPEXP\_CAT*, *UEEXP*) are just a few of various examples alone in the Michigan consumer survey. It is thus not surprising that a whole stream of literature evolved around the question how to accurately quantify the qualitative survey information.

There are two families of methods to quantify qualitative survey information: The regression method, which was introduced by Anderson (1952) and advanced by Pesaran (1985)<sup>3</sup> on the one hand, and the probabilistic approach by Theil (1952) and Carlson and Parkin (1975) often denoted simply as the Carlson-Parkin approach in the literature on the other hand. The method applied here belongs to the latter category. In its base the Carlson-Parkin approach hinges on computing theoretical cutoff-points between the ordered categories in an assumed probability distribution using the share of respondents in the individual categories. The thereby estimated results are just identified up to a scale parameter and have to be calibrated subsequently. For the calibration in its most basic form normally the last observed value from the variable in question is used, as this is assumed to be the value which the respondents had in mind when answering the question about the expected future evolution of the same variable. This approach has four major drawbacks:

1. the cutoff-points (or thresholds) between the three categories (thus between category 1 and 2 as well as between category 2 and 3 in the three category case of the Michigan consumer survey <sup>4</sup>) are by design symmetric around zero (the interval between the two thresholds is often referred to as the “*indifference limens*”, thus the interval in which respondents would notice no change in the variable in question and thus choose category 2)
2. the thresholds are constant over time
3. shortcoming 2. could be circumvented by estimating the thresholds period by period, this however often leads to the problem of zero-responses: the standard Carlson-Parkin approach cannot be estimated if there are no responses in one of the categories
4. the standard Carlson-Parkin approach doesn’t allow to control for heterogeneity among survey participants
5. the standard calibration technique implicitly assumes the unbiasedness of perceptions/expectations and is thus unsuitable to test the rational expectation hypothesis

<sup>3</sup>see also Pesaran (1987) and Pesaran and Weale (2006b)

<sup>4</sup>Berk (1999) proposes a technique for five answering categories, it however has the same shortcomings as the standard Carlson-Parkin approach with three categories.



Kaiser and Spitz (2002) show that the Carlson-Parkin method can be generalized in an ordered probit model (or depending on the distributional assumptions also in an ordered logit model). This allows to solve the problems listed above under points 1. to 4., it however doesn't allow to estimate cross-section specific thresholds. The heterogeneity thereof is only controlled for implicitly by including individual specific variables in the estimation of the ordered probit model. Estimating the ordered probit model with an intercept only is exactly equivalent to the Carlson-Parkin approach (the results are like in the case of the standard Carlson-Parkin approach only identified up to scale and thus have to be calibrated afterwards).

In the context of the present article I am adopting an approach proposed by Lahiri and Zhao (2015) who use an hierarchical ordered probit model (HOPIT) to quantify the qualitative survey expectations<sup>5</sup>. It overcomes the problems outlined above and allows to estimate cross section specific threshold values. As in the paper by Lahiri and Zhao (2015) a time varying parameter model (estimated in a state space framework) is utilized to calibrate the results. This permits to circumnavigate the unbiasedness assumption.

The HOPIT model, also denoted as generalized ordered choice model, was introduced by Eluru et al. (2008) and advanced by Greene and Hensher (2010). It belongs to the family of probabilistic methods and is estimated by maximizing the following likelihood function:

$$\begin{aligned} \mathcal{L}_{HOPIT} = & \sum_{t=1}^T \sum_{i=1}^{N_t} \left\{ I\{y_{it} = 1\} \times \ln \left[ \phi \left( \frac{\delta_{it,1} - y_t^*}{\sigma_{it}} \right) \right] \right\} \\ & + \sum_{t=1}^T \sum_{i=1}^{N_t} \left\{ I\{y_{it} = 2\} \times \ln \left[ \phi \left( \frac{\delta_{it,2} - y_t^*}{\sigma_{it}} \right) - \phi \left( \frac{\delta_{it,1} - y_t^*}{\sigma_{it}} \right) \right] \right\} \\ & + \sum_{t=1}^T \sum_{i=1}^{N_t} \left\{ I\{y_{it} = 3\} \times \ln \left[ 1 - \phi \left( \frac{\delta_{it,2} - y_t^*}{\sigma_{it}} \right) \right] \right\} \end{aligned} \quad (3.25)$$

The difference to the standard ordered probit model is that the latent variable  $y_t^*$ , the lower  $\delta_{it,1}$ , the upper threshold  $\delta_{it,2}$  and the variance  $\sigma_{it}$  are specified on a cross section level by the following equations:

$$y_{it}^* = y_t + \epsilon_{it} \quad (3.26)$$

$$\delta_{it,1} = \gamma_0 + \exp(W_{i,t-h}\beta_{1w}) \quad (3.27)$$

$$\delta_{it,2} = \delta_{it,1} + \exp(W_{i,t-h}\beta_{2w}) \quad (3.28)$$

$$\sigma_{it} = \exp(Z_{i,t-h}\beta_z) \quad (3.29)$$

$W_{i,t-h} \in X_{i,t-h}$  and  $Z_{i,t-h} \in X_{i,t-h}$  represent the model matrices formed from independent variables  $X_{i,t-h}$  in the survey. Both matrices are allowed to have overlappings with regard to the variables they contain.  $y_{it}^*$  is the qualitative responses by individual  $i$  at period  $t$ .  $h$  corresponds to the forecast horizon, which in the context of this article is twelve months. The parameters  $\gamma_0$ ,  $\beta_{1w}$ ,  $\beta_{2w}$  and  $\beta_z$  as well as the thresholds in the

<sup>5</sup>I am grateful to Yongchen Zhao for his helpful comments.

linear latent equation have to be estimated. The formulation of the threshold equations with exponential functions and  $\delta_{it,1}$  in equation (3.27) ensures that the thresholds are ordered. The inclusion of  $\gamma_0$  at the same time allows the thresholds to be negative. To quantify the variable *CPEXP\_CAT* the same parametrization as in the paper by (Lahiri and Zhao, 2015) is used:

- *latent equation*:
  - dummy variables indicating the months covered by the survey since July 1980
- *threshold equation(s)*:
  - PAGO - perceptions with regard to personal finances; please refer to Section 3.1
  - PEXP - expectations with regard to personal finances; please refer to Section 3.1
  - BAGO - perceptions with regard to the general economic conditions; please refer to Section 3.1
  - BEXP - expectations with regard to the general economic conditions; please refer to Section 3.1
  - UEEXP - expectations with regard to the unemployment rate; please refer to Section 3.1
  - RATEX - expectations with regard to the interest rates (categorical)
  - GOVT - evaluation of perceived government performance (categorical)
  - HOM - attitude towards buying real estate (categorical)
  - CAR - attitude towards buying a car (categorical)
  - AGE - age of the respondent (continuous)
  - INCOME - income in USD of the respondent (continuous)
  - SEX - gender of the variable (categorical)
  - EDUC - education level of the respondent (categorical)
- *variance equation*:
  - BAGO
  - UEEXP
  - RATEX
  - GOVT
  - AGE
  - SEX
  - EDUC



– RACE - as defined by the respondent (categorical)

For the estimation of the expectation variable with regard to the unemployment rate only the roles of *CPEXP\_CAT* and *UEEXP* were exchanged. The likelihood function was implemented in *C++*<sup>6</sup>, and augmented by an auto-differentiation algorithm (Fournier et al., 2012) to speed up convergence of the likelihood estimation. The whole procedure comprises the estimation of in both cases 482 parameters. The parameter estimates can be found in Appendix 3.D. In order to ensure that the same parameters have the same effect on the upper and lower threshold but to allow divergence if the effects are indeed significantly different a soft, differentiable penalty function was integrated.

As it is often the case for non-linear models of this magnitude the resulting Hessian matrix is not invertible. A numerical trick using the the general inverse and a general Cholesky decomposition proposed by Gill and King (2004) is applied to compute the standard errors anyway<sup>7</sup>.

### 3.3.2 Calibration

As mentioned before the result  $\tilde{y}_t^*$  obtained by the HOPIT method outlined in the previous subsection are only identified up to scale. The results thus have to be calibrated. In order to render the results suitable for testing the rational expectation hypothesis, a calibration via a time varying parameter model with *AR*(1) structure as suggested by (Lahiri and Zhao, 2015) is utilized. Although this study doesn't contain a rationality test in the normal fashion, for reasons discussed in the last subsection it seems appropriate to avoid the unbiasedness assumption. The time varying parameter model can be written in form of a state space model:

$$\begin{aligned} \text{measurement equation: } p_t &= \beta_t \tilde{y}_t^* \\ \text{transition equation: } \beta_t &= \alpha + \gamma \beta_{t-1} + \epsilon_t \end{aligned}$$

Here  $p_t$  is the reference value for the estimated variable. In the case of the estimation of the expected inflation rate and the expected unemployment rate these variables are the latest observed inflation and unemployment rates respectively. The first order Markov process in the transition equation (the autoregressive term *AR*(1)) ensures a smooth evolution of states over time and thus of the relationship between the raw estimates from the HOPIT model and the reference variable. The serially uncorrelated Gaussian disturbance term  $\epsilon$  with mean zero captures transitory shocks. The final calibrated quantified estimates of the variables in questions eventually are the twelve month ahead forecasts of  $p_t$ . The monthly means of the threshold variables obtained by the cross section specific estimates  $\delta_{it,1} = \gamma_0 + \exp(W_{i,t-h}\beta_{1w})$  and  $\delta_{it,2} = \delta_{it,1} + \exp(W_{i,t-h}\beta_{2w})$  are subsequently rescaled proportionally. The thereby calibrated, monthly threshold

<sup>6</sup>For the source code the reader is referred to Appendix 3.C.

<sup>7</sup>Be  $H^{-1}$  the general inverse of the Hessian matrix and  $V = GCHOL(H^{-1})$  the Cholesky decomposition thereof, then  $V'V$  is the pseudo-variance matrix which can subsequently be used to compute the standard errors and the p-values.



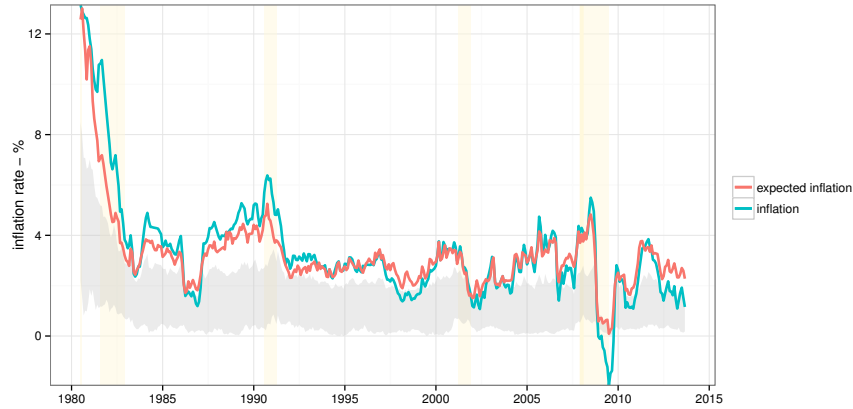


Figure 3.1: Quantification of qualitative expectations of the inflation rate with the HOPIT method (the shaded areas in the plot correspond to the recession periods along the definition of the Federal Reserve Bank)

means  $\bar{\delta}_{t,1}^c$  and  $\bar{\delta}_{t,2}^c$  are then used to rescale the cross section specific estimates  $\delta_{it,1}$  and  $\delta_{it,2}$ . Figure 3.1 and Figure 3.2 display the thereby estimated quantified expectations of the inflation and unemployment rate and compare these values to the actual measured variables. The grey ribbon represents in both cases the indifference limens, thus the area between the lower and the upper threshold in which the respondent (in the plots naturally only the means can be displayed) doesn't notice a change and would thus choose category two. That the line is mostly above the indifference limens indicates that in most periods the majority of respondents chose category three.

### 3.3.3 Converting the realized values into individual specific perception estimates

Using the method outlined above the calibrated thresholds  $\delta_{it,1}^c$  and  $\delta_{it,2}^c$  are now available on an individual level for both the inflation and the unemployment rate. This information can be utilized to recode the realized values in order to obtain individual-specific perception estimates. This is done by comparing the reference variable from twelve months ahead  $p_{t+12}$  with the calibrated individual specific threshold estimates  $\delta_{it,1}^c$  and  $\delta_{it,2}^c$ . If  $p_{t+12} < \delta_{it,1}^c$  the perception variable is coded as 1, if  $\delta_{it,1}^c \leq p_{t+12} \leq \delta_{it,2}^c$  as 2 and if  $\delta_{it,2}^c < p_{t+12}$  as 3. Thereby one obtains estimates for the variables *CPPER\_CAT* and *UEPER*.

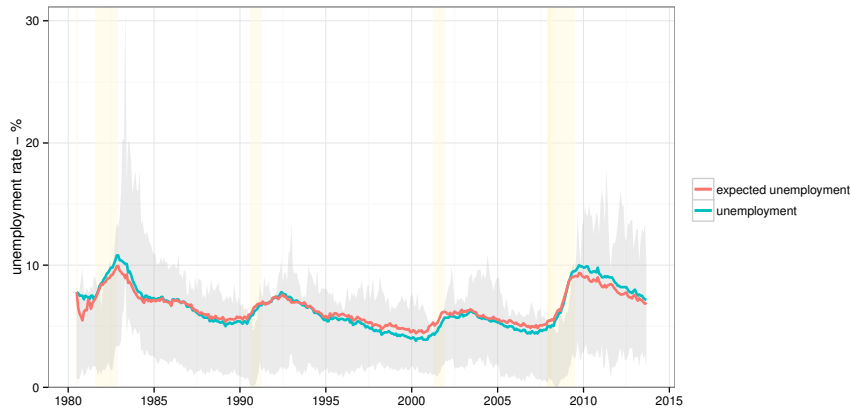


Figure 3.2: Quantification of qualitative expectations of the unemployment rate with the HOPIT method (the shaded areas in the plot correspond to the recession periods along the definition of the Federal Reserve Bank)

### 3.3.4 Partitioning the survey population into rational and non-rational individuals

With individual specific estimates for the perception variables *CPPER\_CAT* and *UEPER* at hand, one can now move on to evaluate the expectational rationality of individual survey respondents. It has to be noted that this doesn't involve a rationality test of the type which standardly can be found in the literature, normally applied to aggregate data. It however allows to partition the survey population into two groups:

1. A group with individuals whose expectations correspond to their perceptions twelve months later.
2. A group with individuals who are either too optimistic or pessimistic in their expectations if one compares them with their perceived values twelve months later.

An individual is considered to have rational expectations for a specific variable if the following conditions are fulfilled respectively:

$$\begin{aligned}
 BEXP - BAGO &= 0 \\
 PEXP - PAGO &= 0 \\
 CPEXP\_CAT - CPPER\_CAT &= 0 \\
 BEXP - BAGO &= 0 \\
 UEPER - UEEXP &= 0
 \end{aligned}$$

For the sake of comparability with the other variables the equation was reversed in the case of unemployment. It is interesting to look at the evolution of these differences or

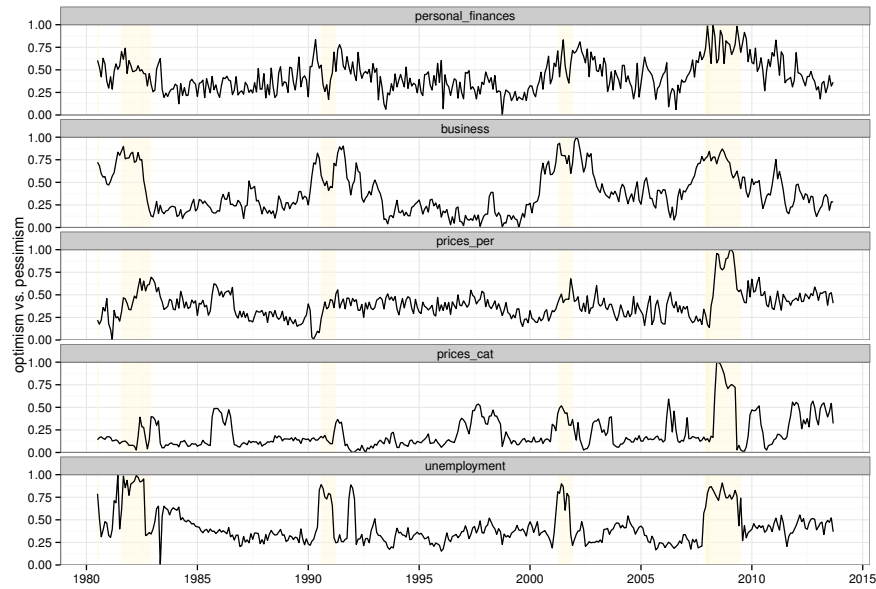


Figure 3.3: Optimism, Pessimism and Rationality over time (the shaded areas in the plot correspond to the recession periods along the definition of the Federal Reserve Bank)

better their respective average over time. They are displayed in Figure 3.3. Looking at Figure 3.3 there are two striking features:

1. There is a noticeable correlation between the variables and
2. the degree of overstated expectations is especially high during phases of recession, marked by the light red shade in the plots.<sup>8</sup>

It might seem counter-intuitive that an overstatement of inflation expectations is regarded as optimistic attitude. This is however in line with economic theory and empirical findings: Higher growth goes hand in hand with an upward pressure on prices. This relation seems to be one which also the respondents of the Michigan consumer survey seem to have internalized.

With these grouping variables at hand one can now proceed to investigate the differences between rational individuals on the one hand and optimistic/pessimistic individuals on the other hand using the extended Oaxaca-Blinder decomposition methods outlined in Section 3.2. For the quantitative expectation variable  $CPEXP\_PER$  and  $CPPER\_PER$  the condition  $CPEXP\_CAT - CPPER\_CAT = 0$  is used as a rationality indicator.

<sup>8</sup>For the recession dates information from the National Bureau of Economic Research (NBER) was used: <https://research.stlouisfed.org/fred2/series/USREC>

## 3.4 Results & Conclusion

The results of the Oaxaca-Blinder methods are displayed in Tables 3.2 to 3.11 in Appendix 3.A of this chapter. The two result tables per variable-group corresponds to the detailed Oaxaca-Blinder method by reference-group and the Neumark pooled regression method respectively. The results are evaluated and interpreted in what follows by the different components of the decomposition results: differences, endowment and coefficients:

### 3.4.1 Differences

What can be observed in the upper part of the results tables in Appendix 3.A is that the group of non-rational respondents along the definition from the last section systematically overestimates the variables in question. The difference values are with the exception of the decomposition with regard to the expected unemployment rate all negative. In the case of the unemployment rate the interpretation has to be reversed as we had previously switched the rationality conditions for coherence reasons (the unemployment rate is the only variable under consideration in which a lower value corresponds to a more optimistic attitude; for further information the reader is referred to Section 3.3.4). The respective result is thus not a contradiction: One could state that the rational agent is in general less optimistic /more pessimistic than the greater number of non-rational survey respondents. This effect is especially pronounced when looking at the Tables 3.2 and 3.3 which compare the quantitative expectation values with regard to inflation to the realized inflation. As noted above, these values have to be interpreted with caution as in this case no real perception values are available and thus only the realized inflation rates were used. The conclusion however stays the same. For the other variables the rationality bias lies between 0.027 and 0.064.

### 3.4.2 Endowment effects, coefficient effects

The main result of this paper is, that the rationality bias can be significantly and to a large extent explained by endowment effects. Sometimes the literature refers to this part as the explained part, while the coefficient effects are denoted as the unexplained part, as it cannot be explained by the explanatory variables included in the estimation. In the gender wage gap literature from which this method originally comes, the explained part is seen as the part of the difference between male and female wages which can be explained by differences in education, work experience (due to pregnancy women often have less working years) etc.. The coefficient effects are unexplained however and can thus be interpreted as due to discrimination.

In the context of this article the endowment part can be interpreted as the part of the differences between rational and non-rational agents which can be explained by the data. The rest (the coefficient effects) must be seen as some kind of unexplained bias which influences the expectation formation of agents. These could be for example personal circumstances which can of course not be covered in full detail by a study as



the Michigan consumer survey. The endowment effects reach from 16% as far as the non-linear decomposition of consumer price expectations are concerned to up to around 60% as far as business climate and unemployment rate expectations are concerned. In all these cases the endowment effects are highly significant. More caution has to be applied in interpreting negative signs before the endowment percentages in the non-linear decomposition of rationality biases for consumer prices and personal finances: It signifies some kind of potential difference between the group of rational and non-rational agents. As mentioned before, the signs in front of the difference values<sup>9</sup> imply that the group of non-rational agents in average tends to be more optimistic relative to the group of rational-agents, this means their expectations overstate the reality as perceived twelve months later.

The negative sign in front of the percentages imply that this effect would be even greater for the concerned variables if the rational agents would have the same sociodemographic characteristics. Considering the notion of heterogeneity in expectations it might not be surprising that this effect is observable when decomposing the rationality bias for variables as individually specific as consumer prices (the experience of prices changes of course very much depends on ones consumption behavior) and personal finances. What all this means in detail will be seen when taking a closer look at the coefficients in the endowment effects. For the decomposition the following variables were included:

- sex - the gender of the respondent (categorical)
- white - dummy variable indicating a respondent is white
- egrade - years of education (continuous, centered)
- workingage - dummy variable indicating if a respondent is below 65 years old and could thus be attributed to the labor force
- income - income in USD (continuous, centered)
- news1 and news2 - dummy variable indicating if the respondent has perceived positive or negative news with regard to the economy prior to interview

Going systematically from upside down, the following interpretation can be given for the coefficient estimates in the detailed Oaxaca-Blinder decomposition. One has to note that the interpretation is given in terms of the effect on the rationality bias since this seems more natural, especially as the sign for the unemployment decomposition are reversed which could create confusion. A positive percentage next to a coefficient thus implies that the effect described above (the group of non-rational individuals being overly optimistic when compared to the group of rational agents), while a negative percentage implies a weakening effect on the rationality bias.

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<sup>9</sup>They were negative for several decomposition results with the exception of unemployment, since for the latter we swapped directions for the rationality condition; for more information please refer to the last Subsection as well as Section 3.3.3.



Being male (sex1) has a positive percentage contribution for the rationality bias for all decomposition results. It thus increases the above described gap between rational and non rational agents. The results for the variable indicating if a respondent is white increases the gap for consumer prices (in the linear case), business climate and the unemployment rate. The opposite is true for personal finances and the consumer prices (non-linear case). Education increases the gap for consumer prices (linear case), consumer prices (non-linear case when using coefficient pooling is used: Neumark), personal finances, business climate and the unemployment rate. The opposite is true for the other variables. Being in the labor force, thus below age 65 (workingage1), has a widening effect on the gap with exceptions for the variables consumer prices (linear and non-linear with the reference group method) and personal finances. The respondents income has a reinforcing effect on the gap for all variables with the exception of consumer prices (non-linear case, reference group), business climate and unemployment. Last but not least, the perception of news (bad or good) has a very strong and significant re-enforcing effect on the rationality gap in general. This is especially true for the variables unemployment and business climate, thus in short for variables which can only be evaluated by individuals using external information, thus news.

The unexplained effects (coefficient effects) seem to play a role, which however cannot be accurately evaluated by the data for most of the variables, i.e. they are not satisfyingly significant in all the cases. The only decomposition results which indicate a “better” measurable contribution of unobserved effects are consumer prices (non-linear case, reference group), personal finances and business climate. Again these results might be attributed to the fact that these variables can be considered as highly subjective.

### 3.4.3 Conclusion and Policy implications

It can be concluded that differences in rationality within the survey population comprised in the data set of the Michigan consumer survey available at the time this study was conducted can be to a large and significant extent explained by the sociodemographic status of an individual represented by gender, race, age, income, education or information about the individuals supplied with the survey (inter alia news consumption) in the above estimations. With regard to variables which are somehow outside of the daily experience horizon for most individuals (for example unemployment and business climate), the effect of news perception is especially strong. The unexplained part, due to unobserved individual effects, on the other hand can unfortunately only be quantified in a very inaccurate manner: The tendencies however tell a similar story. The only variables where the unobserved effects can be measured with halfway acceptable precision are highly subjective in character, namely consumer prices and personal finances.

Overall the findings outlined above point in a similar direction as the results of Chapter 2 where I found a significant anti-herding behavior of agents in their expectation formation with regard to inflation. This anti-herding behavior which corresponds to a bias away from the consensus expectation can be interpreted as due to a differentiated consumption behavior among agents which is also reflected in different expectations as far as the future evolution of prices is concerned. This, as stated above, supports the



hypothesis of heterogenous expectations. The two most important points which can be drawn from the findings in this chapter have similar implications:

1. The accuracy of expectations with regard to objectively measurable realized variables highly depends on the individuals sociodemographic status or expressed differently, the difference between, along the here used definition, “rational” and “non-rational” is largely explainable by data. The notion of rationality in this context might thus be not appropriate as the rationality bias seems to depend mostly on the sociodemographic background of agents.
2. For expectations with regard to variables as consumer prices or personal finances, which, as argued above, very much reflect the subjective experience horizon of an agent this effect is weaker. In these cases one might assume that individual factors play a role which cannot be captured by a standardized household survey. A deviation from the here used rationality condition as far as the survey question with regard to personal finances is concerned, could be for example due to a shock to the individual financial situation of an agent, which could impossibly have been foreseen at the time when the first interview was conducted (in this context one might think about costly maintenance work for housing or vehicles, or since this study uses data from the United States of America, unexpected high medical bills).

Support for the hypothesis of heterogenous expectations, both empirically and experimentally, can be also found in the literature. Mankiw et al. (2004) find with data from various sources, one of which is the Michigan Consumer survey, that there is substantial disagreement among agents with regard to inflation expectations varying in different economic situations. Branch (2004) shows, as well using inflationary expectation data from the Michigan Consumer Survey, that agents choose from a set of different costly predictor functions when forming their beliefs with regard to inflation in the next twelve months. Hommes (2011) chooses a similar approach trying to fit different forecasting heuristics to data from a “*Learning-to-Forecast Experiment*”. It is shown that homogeneous expectation models are, independent from the market setting, inappropriate to fit the data gained from the experiment. Effective learning and thus convergence to the rational expectation condition only occurred when using a cobweb market framework with negative learning feedback similar to that used by Muth (1961) in his seminal paper. These two papers connect to earlier contributions by for example Frankel and Froot (1987, 1990) or Taylor and Allen (1992) who show that professional forecasters employ different techniques to predict future exchange rates. Capistrán and Timmermann (2009) find evidence that the degree of heterogeneity among professional forecasters with regard to future inflation underlies a strong variation over time which magnitude depends on the level as well as the volatility of inflation. The only study which, to the knowledge of the author, relates the notion of heterogenous expectations to the sociodemographic background by consumers is by Pfajfar and Santoro (2009). Concentrating as well on expectations with regard to inflation expectations, the authors find evidence that consumers rather concentrate on the CPI relevant for their sociodemographic subgroup



than on the general future inflation rate as it is surveyed by consumer surveys as the University of Michigan Consumer survey.

The findings outlined above are relevant for policy makers as well as for researchers. On the one hand variables which turn out to be especially susceptible to individually specific effects (as mentioned above expectations with regard to personal finances and inflation fall in this category) are of very high relevance for policy decisions and announcements thereof, especially with regard to monetary policy. They are highly subjective thus hard to assess for policymakers. More research is therefore needed to investigate the rationality bias in these topical areas, as a one-fits all policy could have unintended effects for some parts of the society. For researchers the results indicate a row of other interesting questions: Can the focus on “rational” agents lead to better forecasts of realized variables, be it inflation or household consumption? What could be possible factors for the rationality bias which cannot be explained by the data (corresponding to the unexplained part in the results)? The next Chapter 4 tries to contribute to this debate by evaluating the role of social influences on the expectations formation.



## 3.A Decomposition Results

### Consumer Prices (linear)

	Diff.	StdErr	z-value	Pr(> z )	Pct.	overall Pct.
Difference	-0.724				100	
Endowment	-0.145	0.193	-0.749	0.847	19.985	
Coefficients	-0.579	26.664	-0.022	0	80.015	
Endowment: detail						
sex1	0.078	0.008	10.013	0.994	-10.761	2.712
sex2	-0.098	0.039	-2.494	0.969	13.472	
white1	-0.002	0.001	-3.681	1.000	0.279	0.279
egrade	-0.074	0.081	-0.916	0.935	10.259	10.259
workingage1	0.005	0.010	0.471	0.992	-0.669	-0.669
income	-0.043	0.163	-0.263	0.870	5.915	5.915
news1	0.004	0.012	0.307	0.990	-0.521	1.490
news2	-0.015	0.015	-0.951	0.988	2.010	
Coefficient: detail						
sex1	-0.194	0.819	-0.237	0.413	26.785	45.701
sex2	-0.137	1.039	-0.132	0.299	18.916	
white1	-0.086	2.482	-0.034	0.013	11.807	11.807
egrade	-0.003	29.087	-0.0001	0	0.455	0.455
workingage1	-0.265	1.182	-0.224	0.237	36.568	36.568
income	0.113	2.296	0.049	0.022	-15.638	-15.638
news1	0.011	5.957	0.002	0	-1.477	1.122
news2	-0.019	2.581	-0.007	0.010	2.598	

Table 3.2: Linear decomposition of the expectation bias - consumer prices (reference group)

	Diff.	StdErr	z-value	Pr(> z )	Pct.	overall Pct.
Difference	-0.724				100	
Endowment	-0.207	0.077	-2.684	0.939	28.587	
Coefficients	-0.517	15.049	-0.034	0	71.413	
Endowment: detail						
sex1	0.081	0.005	17.267	0.996	-11.229	2.586
sex2	-0.100	0.010	-10.302	0.992	13.816	
white1	-0.002	0.0005	-3.981	1.000	0.253	0.253
egrade	-0.075	0.021	-3.553	0.983	10.298	10.298
workingage1	-0.006	0.009	-0.648	0.993	0.766	0.766
income	-0.094	0.068	-1.391	0.946	13.032	13.032
news1	0.005	0.008	0.587	0.994	-0.659	1.651
news2	-0.017	0.007	-2.549	0.995	2.311	
Coefficient: detail						
sex1	-0.182	1.408	-0.129	0.159	25.102	39.913
sex2	-0.107	2.473	-0.043	0.013	14.811	
white1	-0.087	5.036	-0.017	0	12.057	12.057
egrade	-0.013	15.639	-0.001	0	1.728	1.728
workingage1	-0.256	1.595	-0.161	0.111	35.384	35.384
income	0.127	4.182	0.030	0.00003	-17.594	-17.594
news1	0.015	8.956	0.002	0	-2.062	-0.075
news2	-0.014	6.984	-0.002	0	1.987	

Table 3.3: Linear decomposition of the expectation bias - consumer prices (Neumark)

## Consumer Prices (non-linear)

	Diff.	StdErr	z-value	Pr(> z )	Pct.	overall Pct.
Difference	-0.016				100	
Endowment	0.004	0.002	1.646	0.998	-24.402	
Coefficients	-0.020	0.175	-0.117	0.861	124.402	
Endowment: detail						
sex1	-0.0001	0.0001	-1.078	1.000	0.841	0.841
white1	0.00003	0.00003	1.021	1.000	-0.160	-0.160
egrade	0.0004	0.0002	1.830	1.000	-2.549	-2.549
workingage1	0.001	0.0003	1.796	1.000	-3.456	-3.456
income	0.003	0.002	1.556	0.998	-20.642	-20.642
news1	-0.0002	0.0002	-1.023	1.000	1.226	1.564
news2	-0.0001	0.0002	-0.287	1.000	0.338	
Coefficient: detail						
sex1	0.001	0.148	0.006	0.882	-5.302	-5.302
white1	0.013	0.024	0.531	0.981	-77.021	-77.021
egrade	0.007	0.051	0.127	0.959	-39.622	-39.622
workingage1	-0.053	0.039	-1.383	0.969	323.899	323.899
income	0.027	0.027	0.982	0.978	-163.763	-163.763
news1	-0.006	0.044	-0.131	0.965	34.987	86.211
news2	-0.008	0.025	-0.338	0.980	51.224	

Table 3.4: Non-Linear decomposition of the expectation bias - consumer prices (reference group)

	Diff.	StdErr	z-value	Pr(> z )	Pct.	overall Pct.
Difference	-0.014				100	
Endowment	-0.002	0.001	-2.871	0.999	16.354	
Coefficients	-0.012	0.149	-0.081	0.881	83.646	
Endowment: detail						
sex1	-0.0001	0.0001	-0.804	1.000	0.468	0.468
white1	0.00001	0.00001	0.862	1.000	-0.086	-0.086
egrade	-0.00003	0.0001	-0.222	1.000	0.185	0.185
workingage1	-0.0003	0.0002	-1.751	1.000	2.350	2.350
income	-0.001	0.001	-1.603	0.999	8.317	8.317
news1	-0.0003	0.0002	-1.932	1.000	2.209	5.119
news2	-0.0004	0.0002	-2.632	1.000	2.910	
Coefficient: detail						
sex1	0.002	0.124	0.015	0.901	-12.475	-12.475
white1	0.023	0.029	0.802	0.977	-161.322	-161.322
egrade	0.013	0.046	0.274	0.963	-86.935	-86.935
workingage1	-0.067	0.077	-0.862	0.938	461.668	461.668
income	0.040	0.032	1.247	0.975	-273.728	-273.728
news1	-0.011	0.040	-0.262	0.968	72.763	156.438
news2	-0.012	0.029	-0.416	0.977	83.675	

Table 3.5: Non-Linear decomposition of the expectation bias - consumer prices (Neu-mark)

**Personal Finances (non-linear)**

	Diff.	StdErr	z-value	Pr(> z )	Pct.	overall Pct.
Difference	-0.025				100	
Endowment	0.002	0.003	0.861	0.998	-10.007	
Coefficients	-0.027	12.497	-0.002	0	110.007	
Endowment: detail						
sex1	-0.0005	0.0004	-1.278	1.000	1.973	1.973
white1	0.001	0.0002	2.960	1.000	-2.752	-2.752
egrade	-0.0003	0.0001	-2.176	1.000	1.173	1.173
workingage1	0.005	0.002	2.079	0.998	-20.926	-20.926
income	-0.00002	0.00005	-0.423	1.000	0.077	0.077
news1	-0.0001	0.0001	-0.615	1.000	0.309	10.448
news2	-0.002	0.0005	-5.373	1.000	10.139	
Coefficient: detail						
sex1	0.001	0.420	0.002	0.674	-3.284	-3.284
white1	-0.004	0.031	-0.118	0.975	15.031	15.031
egrade	-0.002	0.031	-0.066	0.976	8.138	8.138
workingage1	-0.030	0.013	-2.246	0.989	122.470	122.470
income	0.00001	12.280	0	0	-0.031	-0.031
news1	-0.001	0.182	-0.004	0.856	2.604	-32.318
news2	0.009	0.015	0.573	0.988	-34.922	

Table 3.6: Non-Linear decomposition of the expectation bias - personal finances (reference group)

	Diff.	StdErr	z-value	Pr(> z )	Pct.	overall Pct.
Difference	-0.026				100	
Endowment	0.002	0.003	0.989	0.998	-9.740	
Coefficients	-0.028	52.698	-0.001	0	109.740	
Endowment: detail						
sex1	-0.002	0.0004	-3.676	1.000	6.116	6.116
white1	0.001	0.0002	3.600	1.000	-3.177	-3.177
egrade	-0.001	0.0002	-5.825	1.000	4.903	4.903
workingage1	0.011	0.002	4.547	0.998	-42.311	-42.311
income	-0.00003	0.00005	-0.606	1.000	0.109	0.109
news1	-0.0001	0.0001	-0.575	1.000	0.296	24.619
news2	-0.006	0.001	-6.821	0.999	24.323	
Coefficient: detail						
sex1	0.001	1.072	0.001	0.284	-2.331	-2.331
white1	-0.003	0.066	-0.050	0.947	12.853	12.853
egrade	-0.002	0.058	-0.034	0.954	7.773	7.773
workingage1	-0.031	0.011	-2.759	0.991	122.278	122.278
income	0	53.465	0	0	0.013	0.013
news1	-0.001	0.254	-0.003	0.800	3.379	-30.846
news2	0.009	0.028	0.317	0.978	-34.225	

Table 3.7: Non-Linear decomposition of the expectation bias - personal finances (Neu-mark)

**Business Climate (non-linear)**

	Diff.	StdErr	z-value	Pr(> z )	Pct.	overall Pct.
Difference	-0.016				100	
Endowment	-0.010	0.0004	-27.664	1.000	61.357	
Coefficients	-0.006	0.168	-0.037	0.867	38.643	
Endowment: detail						
sex1	-0.001	0.001	-2.324	1.000	7.639	7.639
white1	-0.0001	0.0001	-0.384	1.000	0.347	0.347
egrade	-0.0003	0.0001	-2.195	1.000	1.839	1.839
workingage1	-0.001	0.001	-1.364	1.000	4.478	4.478
income	0	0.00004	0.063	1.000	-0.017	-0.017
news1	-0.0002	0.0001	-1.281	1.000	0.989	47.071
news2	-0.007	0.001	-10.346	0.999	46.082	
Coefficient: detail						
sex1	0.0004	0.224	0.002	0.822	-2.581	-2.581
white1	-0.0001	0.221	-0.001	0.825	0.899	0.899
egrade	-0.001	0.024	-0.028	0.981	4.271	4.271
workingage1	-0.008	0.010	-0.806	0.992	50.679	50.679
income	-0.0002	0.134	-0.001	0.893	1.175	1.175
news1	-0.001	0.050	-0.013	0.960	4.002	-15.800
news2	0.003	0.011	0.284	0.991	-19.802	

Table 3.8: Non-Linear decomposition of the expectation bias - business climate (reference group)

	Diff.	StdErr	z-value	Pr(> z )	Pct.	overall Pct.
Difference	-0.016				100	
Endowment	-0.010	0.0003	-35.256	1.000	62.487	
Coefficients	-0.006	0.148	-0.041	0.882	37.513	
Endowment: detail						
sex1	-0.001	0.0004	-3.846	1.000	8.768	8.768
white1	-0.0001	0.0001	-0.531	1.000	0.344	0.344
egrade	-0.0004	0.0001	-4.561	1.000	2.732	2.732
workingage1	-0.0002	0.0004	-0.491	1.000	1.147	1.147
income	0.00001	0.00003	0.290	1.000	-0.055	-0.055
news1	-0.0001	0.0001	-1.570	1.000	0.876	49.550
news2	-0.008	0.0004	-17.229	1.000	48.675	
Coefficient: detail						
sex1	0.0004	0.406	0.001	0.684	-2.283	-2.283
white1	-0.0003	0.199	-0.001	0.843	1.599	1.599
egrade	-0.001	0.041	-0.016	0.967	4.056	4.056
workingage1	-0.008	0.009	-0.837	0.993	46.958	46.958
income	-0.0002	0.210	-0.001	0.834	1.205	1.205
news1	-0.001	0.064	-0.013	0.949	5.000	-14.022
news2	0.003	0.018	0.165	0.985	-19.022	

Table 3.9: Non-Linear decomposition of the expectation bias - business climate (Neu-mark)

## Unemployment Rate (non-linear)

	Diff.	StdErr	z-value	Pr(> z )	Pct.	overall Pct.
Difference	0.017				100	
Endowment	0.010	0.0003	34.335	1.000	60.608	
Coefficients	0.007	0.273	0.024	0.785	39.392	
Endowment: detail						
sex1	0.001	0.001	1.895	1.000	6.014	6.014
white1	0.0002	0.0001	1.745	1.000	1.412	1.412
egrade	0.0001	0.0001	0.476	1.000	0.365	0.365
workingage1	0.001	0.001	1.891	0.999	7.191	7.191
income	-0.00005	0.00004	-1.279	1.000	-0.310	-0.310
news1	0.00005	0.0001	0.399	1.000	0.291	45.935
news2	0.008	0.001	7.916	0.999	45.644	
Coefficient: detail						
sex1	-0.001	0.293	-0.002	0.770	-3.221	-3.221
white1	-0.001	0.046	-0.025	0.963	-6.889	-6.889
egrade	0.001	0.023	0.056	0.982	7.537	7.537
workingage1	0.011	0.015	0.736	0.988	64.519	64.519
income	-0.0002	0.187	-0.001	0.852	-1.375	-1.375
news1	0.0002	0.249	0.001	0.803	1.301	-21.180
news2	-0.004	0.016	-0.237	0.987	-22.481	

Table 3.10: Non-Linear decomposition of the expectation bias - unemployment rate (reference group)

	Diff.	StdErr	z-value	Pr(> z )	Pct.	overall Pct.
Difference	0.017				100	
Endowment	0.011	0.0002	42.397	1.000	62.981	
Coefficients	0.006	0.725	0.009	0.468	37.019	
Endowment: detail						
sex1	0.001	0.0004	3.244	1.000	7.109	7.109
white1	0.0002	0.0001	2.240	1.000	1.351	1.351
egrade	0.0002	0.0001	2.496	1.000	1.405	1.405
workingage1	0.001	0.0004	2.008	1.000	4.821	4.821
income	-0.00005	0.00003	-1.543	1.000	-0.277	-0.277
news1	0.00005	0.0001	0.556	1.000	0.296	48.572
news2	0.008	0.001	15.084	1.000	48.276	
Coefficient: detail						
sex1	-0.0004	0.578	-0.001	0.563	-2.192	-2.192
white1	-0.001	0.068	-0.016	0.946	-6.245	-6.245
egrade	0.001	0.038	0.028	0.970	6.088	6.088
workingage1	0.010	0.012	0.801	0.991	55.992	55.992
income	-0.0002	0.334	-0.001	0.738	-1.035	-1.035
news1	0.0004	0.199	0.002	0.842	2.190	-15.589
news2	-0.003	0.027	-0.112	0.978	-17.779	

Table 3.11: Non-Linear decomposition of the expectation bias - unemployment (Neu-mark)

### 3.B Linear and Non-Linear Blinder-Oaxaca Decomposition in R Code

```

decomp <- function(formula, dfra, spvar, type){
  dfr <- as.data.frame(dfra)
  dfr[, spvar] <- as.factor(dfr[, spvar]) #format splitting variable as factor
  sa <- dfr[dfr[, spvar]==levels(factor(dfr[, spvar]))[1],] #split up the
    samples
  sb <- dfr[dfr[, spvar]==levels(factor(dfr[, spvar]))[2],] #split up the
    samples

  switch(type,
    linear={
      options(contrasts=c('contr.sum','contr.sum')) #contrasts for dummy variables
      a <- lm(formula, data=sa)
      b <- lm(formula, data=sb)
      f <- lm(formula, data=dfr)
      xa <- model.matrix(formula, sa)
      xb <- model.matrix(formula, sb)
      xf <- model.matrix(formula, dfr)
      ca <- coefficients(a)
      cb <- coefficients(b)
      cf <- coefficients(f)
      za <- 0
      zb <- 0
      zf <- 0
      S <- function(x, c){
        res <- x %*% c
        mean(res)
      }

      #Overall decomposition: reference group
      drg_f <- (S(xa, ca) - S(xb, ca)) + (S(xb, ca) - S(xb, cb))
      drg_e <- (S(xa, ca) - S(xb, ca)) #explained
      drg_u <- (S(xb, ca) - S(xb, cb)) #unexplained
      drg_es <- abs(drg_e)/(abs(drg_e)+abs(drg_u)) #share explained
      drg_us <- abs(drg_u)/(abs(drg_e)+abs(drg_u)) #share unexplained

      #Overall decomposition: Neumark
      dnm_f <- (S(xa, ca) - S(xa, cf)) + (S(xb, cf) - S(xb, cb)) + (S(xa, cf) - S(xb, cf))
      dnm_e <- (S(xa, cf) - S(xb, cf)) #explained
      dnm_u <- (S(xa, ca) - S(xa, cf)) + (S(xb, cf) - S(xb, cb)) #unexplained
      dnm_es <- abs(dnm_e)/(abs(dnm_e)+abs(dnm_u)) #share explained
      dnm_us <- abs(dnm_u)/(abs(dnm_e)+abs(dnm_u)) #share unexplained

      #detailed decomposition
      #weight function endowment/explained
      wx <- function(b, x1, x2){
        N <- b * (colMeans(x1) - colMeans(x2))
        D <- sum(N)
        return(N/D)
      }

      #weight function coefficients/unexplained
      wb <- function(x, b1, b2){
        N <- colMeans(xa) * (b1 - b2)
        D <- sum(N)
        return(N/D)
      }
    }
  )
}

```

```

wtsx_drg ← wx(ca, xa, xb) #endowment: reference group
wtsb_drg ← wb(xa, ca, cb) #coefficients: reference group

wtsx_dnm ← wx(cf, xf, xb) #endowment: Neumark
wtsb_dnm ← wb(xf, cf, cb) #coefficients: Neumark

#detailed decomposition
#reference group A
drg_e_d ← drg_e*wtsx_drg
drg_u_d ← drg_u*wtsb_drg

#neumark method
dnm_e_d ← dnm_e*wtsx_dnm
dnm_u_d ← dnm_u*wtsb_dnm

#calculate variance
#dWx/db
dwx_db ← function(b, x1, x2){
  D ← sum(b*(colMeans(x1) - colMeans(x2)))
  dw ← (colMeans(x1) - colMeans(x2))/D - b* (colMeans(x1) - colMeans(x2)) %*% t
    (colMeans(x1) - colMeans(x2)) /D^2
  return(dw)
}

#dWb/db
dwb_db ← function(b1, b2, x){
  D ← colMeans(x)*(b1 - b2)
  dw ← colMeans(x)/D - (colMeans(x) %*% t(colMeans(x))) * (b1 - b2)/D^2
  return(dw)
}

#note: derivative of wb wrt b1 = -derivative of wd wrt b2
drg_dwxdb_v ← dwx_db(ca, xa, xb) #endowment: reference group
drg_dwbdb_v ← dwb_db(ca, cb, xb) #coefficients: reference group

dnm_dwxdb_v ← dwx_db(cf, xf, xb) #endowment: Neumark
dnm_dwbdb_v ← dwb_db(cf, cb, xb) #coefficients: Neumark

#reference group A
drg_ge ← wtsx_drg*(colMeans(S(xa, ca)*xa)-colMeans(S(xb, ca)*xb))+drg_dwxdb_v
  *drg_e
drg_gc_a ← drg_dwbdb_v*drg_u + wtsb_drg*colMeans(S(xb, cb)*xb)
drg_gc_b ← (-1)*drg_dwbdb_v*drg_u + wtsb_drg*colMeans(S(xb, cb)*xb)

dnm_ge ← wtsx_dnm*(colMeans(S(xf, cf)*xf)-colMeans(S(xb, cf)*xb))+dnm_dwxdb_v
  *dnm_e
dnm_gc_f ← dnm_dwbdb_v*dnm_u + wtsb_dnm*colMeans(S(xb, cb)*xb)
dnm_gc_b ← (-1)*dnm_dwbdb_v*dnm_u + wtsb_dnm*colMeans(S(xb, cb)*xb)

vcca ← vcov(a)[1:length(ca), 1:length(ca)] #variance-covariance-matrix beta_a
vccb ← vcov(b)[1:length(cb), 1:length(cb)] #variance-covariance-matrix beta_b
vccf ← vcov(f)[1:length(cf), 1:length(cf)] #variance-covariance-matrix beta_f

#reference group
drg_vcm_e ← drg_ge %*% vcca %*% t(drg_ge)
drg_vcm_c ← drg_gc_a %*% vcca %*% t(drg_gc_a) + drg_gc_b %*% vccb %*% t(drg_gc_b)

drg_vce ← sqrt(sum(drg_vcm_e))

```

```

drg_vcc ← sqrt(sum(drg_vcm_c))

drg_vced ← sqrt(diag(drg_ge %*% vcca %*% t(drg_ge)))
drg_vccd ← sqrt(diag(drg_gc_a %*% vcca %*% t(drg_gc_a) + drg_gc_b %*% vccb %*%
  t(drg_gc_b)))

#Neumark
dnm_vcm_e ← dnm_ge %*% vccf %*% t(dnm_ge)
dnm_vcm_c ← dnm_gc_f %*% vccf %*% t(dnm_gc_f) + dnm_gc_b %*% vccb %*% t(dnm_gc_
  b)

dnm_vce ← sqrt(sum(dnm_vcm_e))
dnm_vcc ← sqrt(sum(dnm_vcm_c))

dnm_vced ← sqrt(diag(dnm_ge %*% vccf %*% t(dnm_ge)))
dnm_vccd ← sqrt(diag(dnm_gc_f %*% vccf %*% t(dnm_gc_f) + dnm_gc_b %*% vccb %*%
  t(dnm_gc_b)))

res_rg ← data.frame(c("Difference", "Endowment", "Coefficients", "Endowment:
  detail", names(cb), "Coefficient: detail", names(cb)))
res_rg ← cbind(res_rg, as.numeric(c(drg_f, drg_e, drg_u, NA, drg_e_d, NA, drg_u_d)))
res_rg ← cbind(res_rg, as.numeric(c(NA, drg_vce, drg_vcc, NA, drg_vced, NA, drg_vccd
  )))
res_rg ← cbind(res_rg, as.numeric(res_rg[, 2]/res_rg[, 3]))
res_rg ← cbind(res_rg, as.numeric(2 * pnorm(-abs(res_rg[, 3]))))
res_rg ← cbind(res_rg, as.numeric(100*res_rg[, 2]/res_rg[, 1, 2]))
colnames(res_rg) ← c("", "Diff.", "StdErr", "z-value", "Pr(>|z|)", "Pct.")
res_rg[, 2:6] ← round(res_rg[, 2:6], 5)

res_nm ← data.frame(c("Difference", "Endowment", "Coefficients", "Endowment:
  detail", names(cb), "Coefficient: detail", names(cb)))
res_nm ← cbind(res_nm, as.numeric(c(dnm_f, dnm_e, dnm_u, NA, dnm_e_d, NA, dnm_u_d)))
res_nm ← cbind(res_nm, as.numeric(c(NA, dnm_vce, dnm_vcc, NA, dnm_vced, NA, dnm_vccd
  )))
res_nm ← cbind(res_nm, as.numeric(res_nm[, 2]/res_nm[, 3]))
res_nm ← cbind(res_nm, as.numeric(2 * pnorm(-abs(res_nm[, 3]))))
res_nm ← cbind(res_nm, as.numeric(100*res_nm[, 2]/res_nm[, 1, 2]))
colnames(res_nm) ← c("", "Diff.", "StdErr", "z-value", "Pr(>|z|)", "Pct.")
res_nm[, 2:6] ← round(res_nm[, 2:6], 5)

res_rg ← cbind(res_rg, NA)
res_nm ← cbind(res_nm, NA)

cs1 ← aggregate(res_rg[5:(4+NROW(ca)), 6], list(gsub("\\d", "", res_rg[5:(4+NROW(ca)
  )), 1)), sum)
cs2 ← aggregate(res_rg[(NROW(res_rg)-NROW(ca)+1):NROW(res_rg), 6], list(gsub("\\d
  ", "", res_rg[(NROW(res_rg)-NROW(ca)+1):NROW(res_rg), 1])), sum)
id ← data.frame(gsub("\\d", "", res_rg[(NROW(res_rg)-NROW(ca)+1):NROW(res_rg)
  , 1]))
names(id) ← "id"
names(cs1)[1] ← "id"
names(cs2)[1] ← "id"
res_rg[5:(4+NROW(ca)), 7] ← merge(id, cs1, sort=FALSE)[2]
res_rg[(NROW(res_rg)-NROW(ca)+1):NROW(res_rg), 7] ← merge(id, cs2, sort=FALSE)[2]
res_rg[5:(4+NROW(ca)), 7][duplicated(res_rg[5:(4+NROW(ca)), 7])] ← NA
res_rg[(NROW(res_rg)-NROW(ca)+1):NROW(res_rg), 7][duplicated(res_rg[(NROW(res_rg)
  )-NROW(ca)+1):NROW(res_rg), 7])] ← NA
names(res_rg)[7] ← "overall Pct."

cs1 ← aggregate(res_nm[5:(4+NROW(ca)), 6], list(gsub("\\d", "", res_nm[5:(4+NROW(ca)
  )), 1)), sum)
cs2 ← aggregate(res_nm[(NROW(res_nm)-NROW(ca)+1):NROW(res_nm), 6], list(gsub("\\d

```

```

      ",", res_nm[(NROW(res_nm)-NROW(ca)+1):NROW(res_nm),1])) ,sum)
id <- data.frame(gsub("\\d", "", res_nm[(NROW(res_nm)-NROW(ca)+1):NROW(res_nm),1]))
names(id) <- "id"
names(cs1)[1] <- "id"
names(cs2)[1] <- "id"
res_nm[5:(4+NROW(ca)),7] <- merge(id, cs1, sort=FALSE)[2]
res_nm[(NROW(res_nm)-NROW(ca)+1):NROW(res_nm),7] <- merge(id, cs2, sort=FALSE)[2]
res_nm[5:(4+NROW(ca)),7][ duplicated(res_nm[5:(4+NROW(ca)),7]) ] <- NA
res_nm[(NROW(res_nm)-NROW(ca)+1):NROW(res_nm),7][ duplicated(res_nm[(NROW(res_nm)-NROW(ca)+1):NROW(res_nm),7]) ] <- NA
names(res_nm)[7] <- "overall Pct."

ans <- list()
ans$res_rg <- res_rg
ans$res_nm <- res_nm
},
oprobit={
options(contrasts=c('contr.sum','contr.sum')) #contrasts for dummy variables
a <- polr(formula, data=sa, method="probit", Hess = TRUE, model=TRUE)
b <- polr(formula, data=sb, method="probit", Hess = TRUE, model=TRUE)
f <- polr(formula, data=dfr, method="probit", Hess = TRUE, model=TRUE)
xa <- model.matrix(formula, sa)[-1]
xb <- model.matrix(formula, sb)[-1]
xf <- model.matrix(formula, dfr)[-1]
ca <- coefficients(a)
cb <- coefficients(b)
cf <- coefficients(f)
za <- a$zeta
zb <- b$zeta
zf <- f$zeta
S <- function(x,z,c){
res <- list()
res[[1]] <- (pnorm(z[1] - x %*% c) - pnorm(- x %*% c))
if (length(z)>2){
for(i in 2:(length(z)-1)){
res[[i]] <- (i)*(pnorm(z[i] - x %*% c) - pnorm(z[i-1] - x %*% c))
}
}
res[[length(z)] <- length(z)*(1 - pnorm(z[length(z)-1] - x %*% c))
mean(unlist(res))
}

drg_f <- (S(xa, za, ca) - S(xb, za, ca)) + (S(xb, za, ca) - S(xb, za, cb))
drg_e <- (S(xa, za, ca) - S(xb, za, ca)) #explained
drg_u <- (S(xb, za, ca) - S(xb, za, cb)) #unexplained
drg_es <- abs(drg_e)/(abs(drg_e)+abs(drg_u)) #share explained
drg_us <- abs(drg_u)/(abs(drg_e)+abs(drg_u)) #share unexplained

dnm_f <- (S(xa, zf, ca) - S(xa, zf, cf)) + (S(xb, zf, cf) - S(xb, zf, cb)) + (S(xa, zf, cf) - S(xb, zf, cf))
dnm_e <- (S(xa, zf, cf) - S(xb, zf, cf)) #explained
dnm_u <- (S(xa, zf, ca) - S(xa, zf, cf)) + (S(xb, zf, cf) - S(xb, zf, cb)) #unexplained
dnm_es <- abs(dnm_e)/(abs(dnm_e)+abs(dnm_u)) #share explained
dnm_us <- abs(dnm_u)/(abs(dnm_e)+abs(dnm_u)) #share unexplained

#detailed decomposition
#weight function endowment/explained
wx <- function(b,x1,x2){
N <- b * (colMeans(x1)-colMeans(x2))
D <- sum(N)
return(N/D)
}

```

```

}

#weight function coefficients/unexplained
wb ← function(x,b1,b2){
  N ← colMeans(xa) * (b1-b2)
  D ← sum(N)
  return(N/D)
}

wtsx_drg ← wx(ca,xa,xb) #endowment: reference group
wtsb_drg ← wb(xa,ca,cb) #coefficients: reference group

wtsx_dnm ← wx(cf,xf,xb) #endowment: Neumark
wtsb_dnm ← wb(xf,cf,cb) #coefficients: Neumark

#detailed decomposition
#reference group
drg_e_d ← drg_e*wtsx_drg
drg_u_d ← drg_u*wtsb_drg

#neumark method
dnm_e_d ← dnm_e*wtsx_dnm
dnm_u_d ← dnm_u*wtsb_dnm

#calculate variance
#dWx/db
dw_x_db ← function(b,x1,x2){
  D ← sum(b*(colMeans(x1) - colMeans(x2)))
  dw ← (colMeans(x1) - colMeans(x2))/D - b* (colMeans(x1) - colMeans(x2)) %*% t
    (colMeans(x1) - colMeans(x2)) /D^2
  return(dw)
}

#dWb/db
dwb_db ← function(b1,b2,x){
  D ← colMeans(x)*(b1 - b2)
  dw ← colMeans(x)/D - (colMeans(x) %*% t(colMeans(x))) * (b1 - b2)/D^2
  return(dw)
}
#note: derivative of wb wrt b1 = -derivative of wd wrt b2

drg_dwxd_b_v ← dw_x_db(ca,xa,xb) #endowment: reference group
drg_dwbdb_v ← dwb_db(ca,cb,xb) #coefficients: reference group

dnm_dwxd_b_v ← dw_x_db(cf,xf,xb) #endowment: Neumark
dnm_dwbdb_v ← dwb_db(cf,cb,xb) #coefficients: Neumark

drg_ge ← wtsx_drg*(colMeans(qnorm(S(xa,za,ca))*xa)-colMeans(qnorm(S(xb,za,
  ca))*xb))+drg_dwxd_b_v*drg_e
drg_gc_a ← drg_dwbdb_v*drg_u + wtsb_drg*colMeans(qnorm(S(xb,za,cb))*xb)
drg_gc_b ← (-1)*drg_dwbdb_v*drg_u + wtsb_drg*colMeans(qnorm(S(xb,za,cb))*xb)

dnm_ge ← wtsx_dnm*(colMeans(qnorm(S(xf,zf,cf))*xf)-colMeans(qnorm(S(xb,zf,
  cf))*xb))+dnm_dwxd_b_v*dnm_e
dnm_gc_f ← dnm_dwbdb_v*dnm_u + wtsb_dnm*colMeans(qnorm(S(xb,zf,cb))*xb)
dnm_gc_b ← (-1)*dnm_dwbdb_v*dnm_u + wtsb_dnm*colMeans(qnorm(S(xb,zf,cb))*xb)

vcca ← vcov(a)[1:length(ca),1:length(ca)] #variance-covariance-matrix beta_a
vccb ← vcov(b)[1:length(cb),1:length(cb)] #variance-covariance-matrix beta_b
vccf ← vcov(f)[1:length(cf),1:length(cf)] #variance-covariance-matrix beta_f

```

```

#reference group
drg_vcm_e <- drg_ge %*% vcca %*% t(drg_ge)
drg_vcm_c <- drg_gc_a %*% vcca %*% t(drg_gc_a) + drg_gc_b %*% vccb %*% t(drg_gc_
b)

drg_vce <- sqrt(sum(drg_vcm_e))
drg_vcc <- sqrt(sum(drg_vcm_c))

drg_vced <- sqrt(diag(drg_ge %*% vcca %*% t(drg_ge)))
drg_vccd <- sqrt(diag(drg_gc_a %*% vcca %*% t(drg_gc_a) + drg_gc_b %*% vccb %*%
t(drg_gc_b)))

#Neumark
dnm_vcm_e <- dnm_ge %*% vccf %*% t(dnm_ge)
dnm_vcm_c <- dnm_gc_f %*% vccf %*% t(dnm_gc_f) + dnm_gc_b %*% vccb %*% t(dnm_gc_
b)

dnm_vce <- sqrt(sum(dnm_vcm_e))
dnm_vcc <- sqrt(sum(dnm_vcm_c))

dnm_vced <- sqrt(diag(dnm_ge %*% vccf %*% t(dnm_ge)))
dnm_vccd <- sqrt(diag(dnm_gc_f %*% vccf %*% t(dnm_gc_f) + dnm_gc_b %*% vccb %*%
t(dnm_gc_b)))

res_rg <- data.frame(c("Difference", "Endowment", "Coefficients", "Endowment:
detail", names(cb), "Coefficient: detail", names(cb)))
res_rg <- cbind(res_rg, as.numeric(c(drg_f, drg_e, drg_u, NA, drg_e_d, NA, drg_u_d)))
res_rg <- cbind(res_rg, as.numeric(c(NA, drg_vce, drg_vcc, NA, drg_vced, NA, drg_vccd
)))
res_rg <- cbind(res_rg, as.numeric(res_rg[, 2]/res_rg[, 3]))
res_rg <- cbind(res_rg, as.numeric(2 * pnorm(-abs(res_rg[, 3]))))
res_rg <- cbind(res_rg, as.numeric(100*res_rg[, 2]/res_rg[, 1, 2]))
colnames(res_rg) <- c("", "Diff.", "StdErr", "z-value", "Pr(>|z|)", "Pct.")
res_rg[, 2:6] <- round(res_rg[, 2:6], 5)

res_nm <- data.frame(c("Difference", "Endowment", "Coefficients", "Endowment:
detail", names(cb), "Coefficient: detail", names(cb)))
res_nm <- cbind(res_nm, as.numeric(c(dnm_f, dnm_e, dnm_u, NA, dnm_e_d, NA, dnm_u_d)))
res_nm <- cbind(res_nm, as.numeric(c(NA, dnm_vce, dnm_vcc, NA, dnm_vced, NA, dnm_vccd
)))
res_nm <- cbind(res_nm, as.numeric(res_nm[, 2]/res_nm[, 3]))
res_nm <- cbind(res_nm, as.numeric(2 * pnorm(-abs(res_nm[, 3]))))
res_nm <- cbind(res_nm, as.numeric(100*res_nm[, 2]/res_nm[, 1, 2]))
colnames(res_nm) <- c("", "Diff.", "StdErr", "z-value", "Pr(>|z|)", "Pct.")
res_nm[, 2:6] <- round(res_nm[, 2:6], 5)

res_rg <- cbind(res_rg, NA)
res_nm <- cbind(res_nm, NA)

cs1 <- aggregate(res_rg[5:(4+NROW(ca)), 6], list(gsub("\\d", "", res_rg[5:(4+NROW(ca)
)), 1)), sum)
cs2 <- aggregate(res_rg[(NROW(res_rg)-NROW(ca)+1):NROW(res_rg), 6], list(gsub("\\d
", "", res_rg[(NROW(res_rg)-NROW(ca)+1):NROW(res_rg), 1])), sum)
id <- data.frame(gsub("\\d", "", res_rg[(NROW(res_rg)-NROW(ca)+1):NROW(res_rg)
, 1]))
names(id) <- "id"
names(cs1)[1] <- "id"
names(cs2)[1] <- "id"
res_rg[5:(4+NROW(ca)), 7] <- merge(id, cs1, sort=FALSE)[2]
res_rg[(NROW(res_rg)-NROW(ca)+1):NROW(res_rg), 7] <- merge(id, cs2, sort=FALSE)[2]
res_rg[5:(4+NROW(ca)), 7][duplicated(res_rg[5:(4+NROW(ca)), 7])] <- NA

```

```

res_rg[(NROW(res_rg)-NROW(ca)+1):NROW(res_rg),7][duplicated(res_rg[(NROW(res_rg)-NROW(ca)+1):NROW(res_rg),7])] <- NA
names(res_rg)[7] <- "overall Pct."

cs1 <- aggregate(res_nm[5:(4+NROW(ca)),6],list(gsub("\\d","",res_nm[5:(4+NROW(ca)),1])),sum)
cs2 <- aggregate(res_nm[(NROW(res_nm)-NROW(ca)+1):NROW(res_nm),6],list(gsub("\\d","",res_nm[(NROW(res_nm)-NROW(ca)+1):NROW(res_nm),1])),sum)
id <- data.frame(gsub("\\d","",res_nm[(NROW(res_nm)-NROW(ca)+1):NROW(res_nm),1]))
names(id) <- "id"
names(cs1)[1] <- "id"
names(cs2)[1] <- "id"
res_nm[5:(4+NROW(ca)),7] <- merge(id,cs1,sort=FALSE)[2]
res_nm[(NROW(res_nm)-NROW(ca)+1):NROW(res_nm),7] <- merge(id,cs2,sort=FALSE)[2]
res_nm[5:(4+NROW(ca)),7][duplicated(res_nm[5:(4+NROW(ca)),7])] <- NA
res_nm[(NROW(res_nm)-NROW(ca)+1):NROW(res_nm),7][duplicated(res_nm[(NROW(res_nm)-NROW(ca)+1):NROW(res_nm),7])] <- NA
names(res_nm)[7] <- "overall Pct."

ans <- list()
ans$res_rg <- res_rg
ans$res_nm <- res_nm
}
)
return(ans)
}

```



### 3.C C++ implementation of the likelihood function

```

#include <TMB.hpp>

template<class Type>
Type objective_function<Type>::operator() ()
{
    //data:
    DATA_MATRIX(threshold);
    DATA_MATRIX(variance);
    DATA_MATRIX(latent);
    DATA_VECTOR(y);

    //parameters:
    PARAMETER(y0);
    PARAMETER_VECTOR(blow);
    PARAMETER_VECTOR(bupp);
    PARAMETER_VECTOR(bvar);
    PARAMETER_VECTOR(blatt);

    //procedures: (transformed parameters)
    using namespace density;
    int i;
    int n = y.size();
    Type nll = 0.0; //initialize negative log likelihood

    vector<Type> lt(n);
    vector<Type> ut(n);
    vector<Type> si(n);
    vector<Type> mu(n);

    lt = y0 + exp(threshold*blow);
    ut = lt + exp(threshold*bupp);
    si = exp(variance*bvar);
    mu = latent * blatt;

    //get negative log likelihood
    for(i=0;i<n;i++) {
        nll -= (y(i)==1)*log(pnorm(lt(i),mu(i),si(i))) + (y(i)==2)*log(pnorm(
            ut(i),mu(i),si(i)) - pnorm(lt(i),mu(i),si(i))) + (y(i)==3)*log
            (1 - pnorm(ut(i),mu(i),si(i)))));
    }

    //add penalty
    for(i=0;i<blow.size();i++) {
        nll -= dnorm(Type(bupp(i)-blow(i)),Type(0),Type(1),true);
    }

    //reports on transformed parameters:
    REPORT(mu);
    REPORT(si);
    REPORT(lt);
    REPORT(ut);
}

```

```
    return nll;  
}
```



### 3.D HOPIT Quantification Results

	par	se	t.value	p.value
yo	-1.523	0.040	-38.066	0
low_pago1	0.410	0.010	41.215	0
low_pago2	0.389	0.0002	1,627.379	0
low_pago3	0.414	0.0002	2,561.407	0
low_pexp2	0.029	0.0004	81.474	0
low_pexp3	0.043	0.0002	264.286	0
low_bago2	-0.017	0.001	-26.972	0
low_bago3	-0.043	0.0003	-144.674	0
low_bexp2	-0.076	0.0004	-211.315	0
low_bexp3	0.047	0.0002	211.280	0
low_uexp2	-0.033	0.0005	-67.047	0
low_uexp3	0.006	0.0003	19.406	0
low_ratex2	-0.232	0.001	-164.588	0
low_ratex3	-0.628	0.005	-126.995	0
low_govt2	-0.017	0.0003	-52.236	0
low_govt3	0.008	0.0003	23.348	0
low_hom2	-0.055	0.002	-29.072	0
low_hom3	-0.048	0.0002	-269.493	0
low_car2	-0.064	0.002	-39.483	0
low_car3	0.020	0.0001	132.792	0
low_age	0.060	0.0001	639.132	0
low_income	0.030	0.00002	1,346.175	0
low_sex2	0.079	0.0002	322.636	0
low_race2	0.102	0.001	150.374	0
low_race3	-0.005	0.002	-2.651	0.008
low_race4	0.182	0.005	39.170	0
low_race5	0.092	0.003	31.390	0
low_educ2	0.036	0.002	20.588	0
low_educ3	0.001	0.001	1.584	0.113
low_educ4	0.047	0.0003	139.569	0
low_educ5	0.024	0.0003	74.189	0
low_educ6	-0.007	0.0004	-17.044	0
upp_pago1	-0.246	0.002	-102.795	0
upp_pago2	-0.196	0.0001	-2,174.754	0
upp_pago3	-0.216	0.0001	-4,089.948	0
upp_pexp2	0.118	0.0002	657.435	0
upp_pexp3	0.123	0.0001	2,369.980	0
upp_bago2	0.104	0.0001	893.733	0
upp_bago3	0.077	0.0001	1,450.841	0
upp_bexp2	0.188	0.0001	1,429.495	0
upp_bexp3	0.133	0.0001	2,175.378	0
upp_uexp2	0.010	0.0001	124.870	0
upp_uexp3	-0.128	0.0001	-1,725.266	0
upp_ratex2	0.147	0.0001	1,449.516	0
upp_ratex3	0.135	0.0001	2,002.974	0
upp_govt2	0.085	0.0001	1,039.009	0
upp_govt3	0.163	0.0001	2,735.300	0
upp_hom2	0.036	0.001	45.821	0
upp_hom3	0.067	0.0001	950.244	0
upp_car2	0.095	0.0004	213.216	0
upp_car3	0.048	0.0001	865.442	0
upp_age	-0.039	0.00002	-2,490.139	0
upp_income	0.009	0.00001	814.919	0
upp_sex2	-0.030	0.00005	-660.993	0
upp_race2	-0.064	0.0002	-303.369	0
upp_race3	0.019	0.0003	61.332	0
upp_race4	-0.205	0.002	-84.341	0
upp_race5	-0.026	0.001	-35.295	0
upp_educ2	-0.146	0.0004	-335.262	0
upp_educ3	-0.098	0.0001	-726.369	0
upp_educ4	-0.136	0.0001	-1,707.978	0
upp_educ5	-0.105	0.0001	-1,627.898	0
upp_educ6	-0.091	0.0001	-1,134.752	0
var_bago1	-0.018	0.001	-14.736	0
var_bago2	-0.075	0.0003	-288.817	0
var_bago3	-0.033	0.0001	-306.349	0
var_uexp2	-0.094	0.0002	-532.964	0
var_uexp3	-0.054	0.0001	-501.206	0
var_ratex2	-0.037	0.0002	-190.451	0
var_ratex3	0.058	0.0001	592.164	0
var_govt2	0.024	0.0001	194.260	0
var_govt3	0.081	0.0001	578.005	0
var_age	-0.011	0.00003	-439.471	0
var_sex2	-0.084	0.0001	-913.432	0
var_race2	0.067	0.0003	210.576	0
var_race3	0.086	0.001	147.253	0
var_race4	0.033	0.003	11.552	0
var_race5	0.058	0.002	38.284	0
var_educ2	-0.029	0.0004	-69.315	0
var_educ3	-0.079	0.0001	-833.864	0
var_educ4	-0.091	0.0001	-863.611	0
var_educ5	-0.111	0.0001	-949.992	0
var_educ6	-0.135	0.0002	-777.518	0

Table 3.12: HOPIT parameter estimates: consumer prices

	par	se	t.value	p.value
yo	-1.843	0.003	-596.490	0
low_pago1	0.853	0.00004	21,883.930	0
low_pago2	0.859	0	9,260,339,552.000	0
low_pago3	0.859	0	27,379,545,072.000	0
low_pexp2	0.003	0	10,074,949.000	0
low_pexp3	0.031	0	513,131,180.000	0
low_bago2	-0.003	0	-1,382,746.000	0
low_bago3	0.043	0	166,068,607.000	0
low_bexp2	0.045	0	95,554,253.000	0
low_bexp3	0.166	0	164,087,847.000	0
low_cpexp_cat2	-0.020	0	-9,783,589.000	0
low_cpexp_cat3	-0.037	0	-353,660,988.000	0
low_ratex2	-0.011	0	-40,306,471.000	0
low_ratex3	-0.023	0	-213,107,643.000	0
low_govt2	0.047	0	63,446,739.000	0
low_govt3	0.091	0	670,767,816.000	0
low_hom2	0.006	0	929,566.400	0
low_hom3	0.006	0	99,726,075.000	0
low_car2	0.020	0	8,465,307.000	0
low_car3	0.010	0	269,774,700.000	0
low_age	0.015	0	1,603,793,660.000	0
low_income	-0.001	0	-660,647,562.000	0
low_sex2	-0.028	0	-269,554,999.000	0
low_race2	0.007	0	4,584,847.000	0
low_race3	-0.003	0	-324,015.400	0
low_race4	-0.025	0.00000	-122,605.100	0
low_race5	-0.003	0.00000	-94,773.110	0
low_educ2	0.036	0.00000	1,036,937.000	0
low_educ3	0.044	0	13,906,810.000	0
low_educ4	0.047	0	148,315,964.000	0
low_educ5	0.056	0	318,582,468.000	0
low_educ6	0.060	0	367,382,364.000	0
upp_pago1	-0.818	0.00000	-336,528.600	0
upp_pago2	-0.777	0	-133,992,969.000	0
upp_pago3	-0.764	0	-321,497,005.000	0
upp_pexp2	0.117	0	7,939,513.000	0
upp_pexp3	0.056	0	21,549,730.000	0
upp_bago2	0.150	0.00000	8,169,932.000	0
upp_bago3	0.031	0	4,932,221.000	0
upp_bexp2	0.337	0	30,017,677.000	0
upp_bexp3	0.149	0	22,756,903.000	0
upp_cpexp_cat2	0.223	0.00000	1,264,693.000	0
upp_cpexp_cat3	0.201	0	34,564,858.000	0
upp_ratex2	0.074	0.00000	4,086,937.000	0
upp_ratex3	0.080	0	21,296,799.000	0
upp_govt2	0.088	0	15,376,591.000	0
upp_govt3	0.146	0.00000	5,531,247.000	0
upp_hom2	-0.019	0.00000	-34,009.460	0
upp_hom3	0.078	0	22,020,631.000	0
upp_car2	-0.029	0.00000	-132,415.000	0
upp_car3	0.048	0	20,791,894.000	0
upp_age	-0.060	0	-189,795,552.000	0
upp_income	0.014	0	112,188,569.000	0
upp_sex2	0.087	0	25,516,251.000	0
upp_race2	-0.146	0.00000	-2,639,098.000	0
upp_race3	0.028	0.00000	130,954.000	0
upp_race4	0.023	0.00000	8,493.716	0
upp_race5	0.064	0.00000	34,956.960	0
upp_educ2	-0.166	0.00000	-1,216,388.000	0
upp_educ3	-0.181	0	-19,873,753.000	0
upp_educ4	-0.209	0	-31,404,051.000	0
upp_educ5	-0.262	0	-38,577,416.000	0
upp_educ6	-0.307	0	-26,171,842.000	0
var_bago1	-0.218	0.00000	-100,235.000	0
var_bago2	-0.206	0.00000	-5,994,513.000	0
var_bago3	-0.256	0	-41,373,588.000	0
var_cpexp_cat2	-0.047	0.00000	-239,860.000	0
var_cpexp_cat3	-0.023	0	-3,028,405.000	0
var_ratex2	-0.072	0.00000	-2,879,686.000	0
var_ratex3	-0.005	0	-989,296.200	0
var_govt2	-0.012	0	-1,056,967.000	0
var_govt3	0.055	0	4,877,088.000	0
var_age	-0.061	0	-148,819,642.000	0
var_sex2	-0.005	0	-974,558.900	0
var_race2	0.057	0.00000	650,939.300	0
var_race3	0.158	0.00000	642,053.600	0
var_race4	0.053	0.00001	9,070.796	0
var_race5	0.214	0.00000	136,682.000	0
var_educ2	-0.178	0.00000	-1,344,814.000	0
var_educ3	-0.342	0	-88,819,314.000	0
var_educ4	-0.394	0	-71,083,994.000	0
var_educ5	-0.449	0	-66,824,213.000	0
var_educ6	-0.522	0.00000	-31,647,677.000	0

Table 3.13: HOPIT parameter estimates: consumer prices

## Chapter 4

# Expectation Formation and Social Influence<sup>1</sup>

### 4.1 Introduction

#### 4.1.1 Objectives

The Michigan consumer survey as most household surveys today is for the most part based on qualitative questions with regard to the financial/economical situation of the interviewed household or the general economic situation. The latter category of questions is of specific interest for researchers as it allows to make assertions over the formation of expectations, not least because the responses can be compared between households and correspond to measurable variables (inflation, employment, economic growth etc.). Standard topics investigated in this field of research comprehend the rationality and unbiasedness of expectations. The article at hand contributes to the literature addressing the latter question.

Using repeated cross-section data from the University of Michigan consumer survey this article investigates how consumers or agents form their expectation within their social environment. This means how and to what degree agents influence other agents or are influenced by other agents in their expectation formation? Which groups of agents are the most influential and best connected? And on what factors do influence as well as the connectedness and the position within a network of social influence depend?

By applying neural network clustering techniques (*self-organizing Kohonen maps*; see Kohonen (1982)) the cross-section data of the University of Michigan consumer survey is transformed into a pseudo panel. A non-parametric information-theoretic approach from Physics denoted as “*transfer entropy*” (Schreiber, 2000) is then used to measure the information flows between cells (cohorts). The findings show that agents with higher education, higher income and to a certain degree higher age are more influential and better connected than others. It is further shown that the so inferred social network is

---

<sup>1</sup>This chapter bases on a working paper published in the working paper series of the Economics Faculty of the University Paris 1 Panthéon-Sorbonne (Karpf, 2014).



sex	education	n	income		age	
			mean	sd	mean	sd
male	no highschool	10901	22580	24011	52	19
	highschool	52257	41721	38367	44	17
	college	36872	70155	67400	45	15
female	no highschool	14895	15837	17341	56	19
	highschool	69487	34960	33776	46	18
	college	36324	62612	59527	44	15
	All	220736	45088	48698	46	17

Table 4.1: University of Michigan Consumer Survey: Descriptive Statistics

scale free and thus follows a power law distribution.

Approaches to indirectly infer structures of social influence and networks via behavioral data as introduced in this article are new to economics. This is remarkable as social influence and in this context also imitation or conformity are often emphasized as important factors for decisions of economic agents. Contributions to this topic can be traced back to early seminal works by e.g. Sherif (1936), Hyman (1942), Asch (1951), Jahoda (1959) or Merton (1968). This as Manski (2000) points out might be due to the fact that social interactions as object of investigation in economics are often reduced to the market. In consumer research on the other hand social influence is perceived as one of the “... *most pervasive determinants [...] of individual’s behaviour...*” (Burnkrant and Cousineau, 1975). As behavior is strongly shaped by expectations it is believed that it is worthwhile to investigate and understand how information transfer (“*social influence*”) within a society works and which factors determine this influence. For this purpose the University of Michigan consumer survey which captures the evolution of households perceptions and expectations with regard to the economy since 1978<sup>2</sup> seems to be ideal. Technically the paper at hand was inspired by Ver Steeg and Galstyan (2012) who use information theory to expose structures of social influence and networks on the social media network Twitter.

In the following subsection the University of Michigan consumer survey as well as the data set used for the article at hand is described. Section 4.2 introduces *transfer entropy*, the information theoretic measure used to estimate the information flows between different agents or cohorts. Section 4.3 discusses the techniques applied to create a pseudo panel, to estimate information flows and basing on this to infer network connections between agents. Section 4.4 presents and discusses the results.

#### 4.1.2 The Data Set: University of Michigan Consumer Survey

The University of Michigan consumer survey is a household survey conducted by the Survey Research Center of the University of Michigan since 1966. Since 1978 at least 500 representative households from the United States excluding Hawaii and Alaska are

<sup>2</sup>The University of Michigan consumer survey was originally created in 1966. Only since 1978 however the survey is conducted monthly and the core of the questions was unchanged.

selected and surveyed each month about their respective financial situation, buying attitudes as well with regard to their perceptions/expectations regarding the general economic development in the short and long run. Next to this topically specific questions the data set also contains various sociodemographic variables such as education, sex, household size, region of residence, age, household income, etc.. The data set further includes survey weights for each interviewed household. This will be further on useful when correcting for majority effects while estimating the degree of social influence.

The data set available at the time this study was conducted contained around 220,000 observations between July 1980 and June 2013 (after sorting out those without responses in the relevant variables). Descriptive statistics of the data set used can be found in Table 4.1. Within the survey one question is specifically important for the article at hand:

*How about a year from now, do you expect that in the country as a whole business conditions will be better, or worse than they are at present, or just about the same?*

- *Better a year from now*
- *About the same*
- *Worse a year from now*

This question (corresponding to the questionnaire we further on refer to this variable as *BEXP*) is used to measure the information transfer between agents or cells respectively. It was selected as it is very general. A question with regard to expectations about issues like inflation or personal finances for example would have not been suitable, as perceptions/expectations thereof strongly depend on the individuals/households consumption behavior.<sup>3</sup>

## 4.2 Transfer Entropy

The information associated with outcome  $x$  with probability  $p(x)$  of a random variable  $X$  is defined as:

$$I(x) = \log_a \left( \frac{1}{p(x)} \right) = -\log_a(p(x)) \quad (4.1)$$

The smaller the probability of the event the higher is the information content of the event itself. The unit of information depends on the choice of the logarithmic base  $a$ . If  $a = 2$  the unit of  $I(x)$  is *bits*, if  $a = e$  the unit is *nats* and if  $a = 10$  the unit is *hartley*. For the sake of clarity the base will be ignored for now. Basing on (4.1) the *Shannon-Entropy*  $H(x)$  (Shannon, 1948) represents the information entropy of a message which in this context is a row of events of which the combined information corresponds to the sum of single informations multiplied with the respective event probabilities:

$$H(x) = \sum_x p(x)I(x) = -\sum_x p(x)\log(p(x)) \quad (4.2)$$

---

<sup>3</sup>Compare to the results found in Chapters 2 and 3.



For two systems the joint Shannon-Entropy might be written down as,

$$H_D(x, y) = - \sum_{x, y} p(x, y) \log(p(x, y)) \quad (4.3)$$

if independence between  $x$  and  $y$  cannot be assumed or

$$H_I(x, y) = - \sum_{x, y} p(x, y) \log(p(x)p(y)) \quad (4.4)$$

in the case of independence between  $x$  and  $y$ . Basing on (4.3) and (4.4) one can construct a measure for mutual information between the two systems  $x$  and  $y$ , which means the excess amount of information when wrongly assuming independence although the opposite is true:

$$\begin{aligned} M(x, y) &= H_I(x, y) - H_D(x, y) \\ &= - \sum_{x, y} p(x, y) \log(p(x)p(y)) + \sum_{x, y} p(x, y) \log(p(x, y)) \\ &= \sum_{x, y} p(x, y) [\log(p(x, y)) - \log(p(x)p(y))] \\ &= \sum_{x, y} p(x, y) \log \left( \frac{p(x, y)}{p(x)p(y)} \right) \end{aligned} \quad (4.5)$$

*Mutual-Information* is a concept related to the *Kullback-Leibler distance* (also called *relative entropy* or *Kullback-Leibler divergence*) (Kullback, 1959). The *Kullback-Leibler divergence*  $K(x)$  corresponds to excess amount of information when wrongly assuming a probability distribution  $q(x)$  as opposed to the true distribution  $p(x)$  (Schreiber, 2000). This means it is a measure of distance between two different distributions.

$$K(x) = \sum_x p(x) \log \left( \frac{p(x)}{q(x)} \right) \quad (4.6)$$

The same measure can also be applied to conditional probabilities:

$$K(x|y) = \sum_x p(x, y) \log \left( \frac{p(x|y)}{q(x|y)} \right) \quad (4.7)$$

The problem with the *Mutual Information* measure (4.5) or the *Kullback-Entropy* (4.7) however is that it doesn't incorporate any directional dynamics between the two systems:  $M(x, y) = M(y, x)$  is symmetric. Reformulating  $M(x, y)$  however hints how such a dynamic could be taken into account. It can be shown that  $M(x, y) = H(x) - H(x|y)$  or alternatively due to symmetry  $M(x, y) = H(x) - H(y|x)$ . The Mutual-Information measure can thus be interpreted as a "... reduction in the uncertainty of  $x$  due to the knowledge of  $y$ ." (Cover and Thomas, 1991, p. 20), or the other way around. This points to the related concept of conditional entropy:  $H(x|y) = - \sum p(x, y) \log(p(x|y))$ . One could thus ask if the history of one variable could contribute to its predictability. In

this case one could assume that the random variable follows a  $k^{th}$  order Markov process and write it down in the form of a conditional entropy:

$$H(x_{t+1}|x_t) = - \sum_{x_{t+1}} p(x_{t+1}, x_t^k) \log(p(x_{t+1}|x_t^k)) \quad (4.8)$$

where  $x_t^k = x_t, \dots, x_{t-k+1}$ . This concept can again be extended to two systems  $x$  and  $y$ :

$$H(x_{t+1}|x_t, y_t) = - \sum_{x_{t+1}, x_t, y_t} p(x_{t+1}, x_t^k, y_t^k) \log(p(x_{t+1}|x_t^k, y_t^k)) \quad (4.9)$$

The idea of Schreiber (2000) is now to use the divergence from the Markov property  $p(x_{t+1}|x_t) = p(x_{t+1}|x_t, y_t)$  as a proxy for the information flow between  $y$  and  $x$ .<sup>4</sup> This means one takes the difference between (4.9) and  $H(x_{t+1}|x_t) = - \sum_{x_{t+1}, x_t, y_t} p(x_{t+1}, x_t^k, y_t^k) \log(p(x_{t+1}|x_t^k))$ .

$$\begin{aligned} H(x_{t+1}|x_t) - H(x_{t+1}|x_t, y_t) &= - \sum_{x_{t+1}, x_t, y_t} p(x_{t+1}, x_t^k, y_t^k) \log(p(x_{t+1}|x_t^k)) \\ &\quad + \sum_{x_{t+1}, x_t, y_t} p(x_{t+1}, x_t^k, y_t^k) \log(p(x_{t+1}|x_t^k, y_t^k)) \\ &= \sum_{x_{t+1}, x_t, y_t} p(x_{t+1}, x_t^k, y_t^k) \left( \frac{p(x_{t+1}|x_t^k, y_t^k)}{p(x_{t+1}|x_t^k)} \right) \end{aligned} \quad (4.10)$$

Equation (4.10) is again a kind of Kullback-Leibler entropy denoted by (Schreiber, 2000) as the transfer entropy  $T_{y \rightarrow x}$  which now allows to measure the flow of information from  $y$  to  $x$ . Because of its inherent asymmetry there are two relevant equations:

$$T_{y \rightarrow x} = \sum_{x_{t+1}, x_t, y_t} p(x_{t+1}, x_t^k, y_t^k) \left( \frac{p(x_{t+1}|x_t^k, y_t^k)}{p(x_{t+1}|x_t^k)} \right) \quad (4.11)$$

$$T_{x \rightarrow y} = \sum_{x_{t+1}, y_t, x_t} p(y_{t+1}, y_t^k, x_t^k) \left( \frac{p(y_{t+1}|y_t^k, x_t^k)}{p(y_{t+1}|y_t^k)} \right) \quad (4.12)$$

Equation (4.11) measures the flow of information from  $y$  to  $x$  while equation (4.12) measures the flow of information from  $x$  to  $y$ . In the case one uses a logarithm of base 10 as it is done in the remainder of this article e.g.  $T_{x \rightarrow y}$  corresponds to the amount of digits system  $x$  adds to system  $y$  in terms of predictability.

**Panzeri-Treves bias correction** As Ver Steeg and Galstyan (2012) point out sparse data can lead to a systematic bias of the transfer entropy measures (4.11) and (4.12) derived above. Therefore along the example by Ver Steeg and Galstyan (2012) the empirical bias estimate by Panzeri and Treves (1996) is used to correct for this systematic error. The Panzeri-Treves bias estimate is calculated for the conditional entropies in

<sup>4</sup>The assumption of independence between  $x$  and  $y$  would have again resulted into a symmetric measure.

(4.10) on which the transfer entropy is based and subsequently subtracted from the same respectively:

$$BIAS[H(R|S)] = \frac{-1}{2 \cdot N \cdot \log(2)} \sum_{s \in \text{dom}(S)} (N_s - 1) \quad (4.13)$$

Here  $R$  and  $S$  are the response and the signal respectively. The variable  $N$  denotes the common sample size while  $N_s$  is the number of unique responses for a response  $r \in \text{dom}(R)$ .

**Similarities and Advantages to Granger causality** Barnett et al. (2009) formally show that transfer entropy and Granger causality are equivalent for variables following a Gaussian distribution. This is an assumption which for example is frequently made when quantifying ordinal variables stemming from surveys via the Carlson-Parkin approach (Carlson and Parkin, 1975) or one of it's derivatives. In both Chapter 2 and 3 qualitative survey variables where quantified using an ordinal estimation framework with a probit link function. This is not different from assuming that the underlying latent variable represented in censored ordinal form in the survey follows a Gaussian distribution. In the case a continuous survey variable is available, the application of the standard Granger causality procedure would be in general equivalent to what is described in the following section. The Michigan Consumer Survey indeed contains a question which collects quantitative information about inflation expectations. Three considerations however resulted in the choice to apply the transfer entropy measures directly to the qualitative survey variables: 1) As was already discussed in Chapter 2, it turns out that while interviewees have a good sense about the trend when asked about their expectations with regard to the evolution of economic variables, they often lack a good assessment of the magnitudes. 2) For this reason and the superior efficiency of categorical questions in the practical data collection procedure, ordinal survey questions are still the workhorse for present day survey based Economic research. 3) Last but not least, transfer entropies are a very flexible and computationally efficient way to infer causality- (and, as I will show later, network-) structures, which application is new in the context of empirical research on consumer and business sentiment data.

### 4.3 Measuring Information Flows and Network structures with household surveys

To apply the transfer entropy measure introduced in the last section to e.g. a pair of two agents, a time series of one factor variable has to be available for each of the two agents (in the context of this article this factor variable is going to be the question with regard to business conditions *BEXP* as outlined in section 4.1.2). The University of Michigan consumer survey however unfortunately only exhibits a repeated cross section structure <sup>5</sup> and is hence not directly usable for this purpose. Therefore a pseudo-panel

<sup>5</sup>Only 40% of the survey population are interviewed twice. See Chapter 3.



structure has to be artificially established beforehand. Like in Chapter 2 this is done via neural network clustering (self-organizing Kohonen maps) as opposed to the traditional technique by Deaton (1985).<sup>6</sup>

#### 4.3.1 Construction of a pseudo panel

The panel-structure problem referred to above is addressed by forming a synthetic or pseudo-panel. This technique was originally introduced by Deaton (1985) who uses variables which are not supposed to change over time like sex and birth cohort to group the survey population. The article at hand however applies a neural network clustering technique to construct the pseudo panel which was originally proposed by Gardes et al. (1996). This approach has the following crucial advantages:

1. It permits to incorporate more comprehensive sociodemographic information when building the pseudo panel. Grouping the survey population by variables as for example sex, education and birth cohort results in a large number of rather unbalanced cohorts.
2. The information content of continuous variables as for example income does not have to be artificially reduced by grouping them into different classes as this would be necessary if one used Deaton's approach. Such variables can be used directly in the construction of the pseudo panel when using the neural network approach.
3. Because of the inclusion of more and also continuous sociodemographic variables a pseudo panel constructed by the neural network approach is better balanced.
4. It can be shown that the construction of cohorts via neural networks results in a lower within cohort and a higher between cohort variance than when using the technique by Deaton (Cottrell and Gaubert, 2007).

Following the example by Gardes et al. (1996) and Cottrell and Gaubert (2007) this article therefore uses self-organizing Kohonen maps (Kohonen, 2001) to group the participants within the repeated cross sections into synthetic cohorts. Variables as gender, age, years of school, region of residence, income and race were presented to the algorithm in all in all 1000 iterations to construct a  $8 \times 8$  hexagonal Kohonen map resulting into 64 cells. For the construction of the Kohonen map the “*kohonen*” R-package was used (Wehrens and Buydens, 2007).<sup>7</sup>

The ordinal business expectation variable *BEXP* (see section 4.1.2) which is central within this article was averaged on a cohort level. Since the computation of the transfer entropy demands a discrete variable the cohort means were then transformed into an ordered variable with three categories. For this purpose a discretization approach was chosen which yields approximately similar frequencies (in the whole data set) for each category (Meyer, 2008). This also serves as another remedy to keep the estimation bias

<sup>6</sup>See also Section 2.5.

<sup>7</sup>For another application of the Kohonen algorithm the reader is referred to Chapter 2.



of transfer entropies as low as possible. As was seen in the end of the last section the estimates can be biased by sparse data, which in this context means that not all areas of the probability distributions are observable. Choosing a discretization algorithm which focuses on equal frequencies seems thus appropriate.

### 4.3.2 Computing the Transfer Entropy to infer the structure of a Social Network

The transfer entropy measure for asymmetrical information transfer (see equations (4.11) and (4.12); a bin width  $k$  of one was used) is calculated for each pair of the 64 cohorts (constructed along the technique outlined in the last subsection) in both directions. This results into 4,032 transfer entropy measures, two for every pair of cohorts: Using self organizing Kohonen maps a pseudo panel is established containing all in all 64 cells (or cohorts) available in all periods in which the survey data was available. For each period a cohort-level discrete value corresponding to the original individual-level variable BEXP was computed by averaging and subsequent frequency sensitive discretization procedures (Meyer, 2008). The result are 64 ordinal time series which correspond to the cohort-level expectations with regard to business conditions. Between these time series the respective information flow can be evaluated using transfer entropies. In doing so it is measured to what extent the past values of a random process  $X$  can contribute in the prediction of future values of a random process  $Y$  given the its own history. In simple words: what can one say about the next draw of a random variable considering its last outcomes, and how could the consideration of another random variable and its respective history help in predicting the outcome of this draw. To avoid majority effects the active transfer entropy measures are corrected by means of the survey weights of the respective cohorts as well as the cohort size. This means the outgoing information transfer of cohorts with high survey/cohort weights has been revised downwards, while the outgoing information transfer of cohorts with small survey/cohort weights has been revised upwards. Additionally the balance of outgoing and incoming information transfer was computed.

## 4.4 Results

### 4.4.1 Summary

Table 4.2 and 4.3 present an overview of the results. In both tables three variables are displayed: the average outgoing information, the average incoming information as well as the balance of these two variables for the respective subgroups listed on the left. The higher the balance number the more influential the respective subgroup is. Especially in Table 4.2 it is striking that the social influence of cohorts/individuals increases with education and income: While cohorts with a mean income below USD 20,000 are net receivers of information the other income groups are net senders of information. The degree of net sent information is increasing with the average income. As far as education is concerned the most influential group is that with between fifteen and twenty years of



		outgoing mean	incoming mean	balance mean
income	(0,200000]	0.04741	0.05687	-0.00946
	(200000,400000]	0.27922	0.05601	0.22321
	(400000,600000]	0.45811	0.09464	0.36347
age	(20,40]	0.03554	0.05677	-0.02124
	(40,60]	0.08890	0.06030	0.02860
	(60,80]	0.03661	0.05332	-0.01672
education	(5,10]	0.06920	0.05174	0.01746
	(10,15]	0.03323	0.05685	-0.02362
	(15,20]	0.08178	0.05990	0.02189
	All	0.05745	0.05745	0.00000

Table 4.2: Transfer Entropies: split up by education and age

age	education	outgoing mean	incoming mean	balance mean
(20,40]	(5,10]	0.07977	0.05020	0.02957
	(10,15]	0.03351	0.05672	-0.02321
	(15,20]	0.03382	0.05771	-0.02389
(40,60]	(5,10]	0.09651	0.04659	0.04992
	(10,15]	0.03935	0.06188	-0.02254
	(15,20]	0.12526	0.06224	0.06302
(60,80]	(5,10]	0.04607	0.05598	-0.00991
	(10,15]	0.02017	0.04722	-0.02704
	(15,20]	0.04548	0.05731	-0.01184

Table 4.3: Transfer Entropies: by income, education and age

schooling. The group with ten to fifteen years of schooling are net receivers of information where the balance of received and sent information is negative and in absolute terms approximately corresponds to the positive balance value of the group with between fifteen and twenty years of schooling. The cohorts with the lowest education in contrast have a positive balance value. This as one will see later on might be explained by some kind of majority effect which persists in spite of the correction by survey and cohort weights outlined above. As far as age is concerned the most influential groups are those with an average age of between forty and sixty years. This is also reflected in the more detailed Table 4.3. The most influential agents are between 40 and 60 years old and hold at least a college degree.

#### 4.4.2 Identifying information transfer between social groups

The method outlined in section 4.3.2 supplies a list of transfer entropies for each pair of cohorts in both directions. This alone however only permits to present rather superficial results as they were shown in the last section. To allow a better assessment on how information is transmitted within and between different social groups and to make this transmission of information better visible local regressions (locally weighted scatterplot



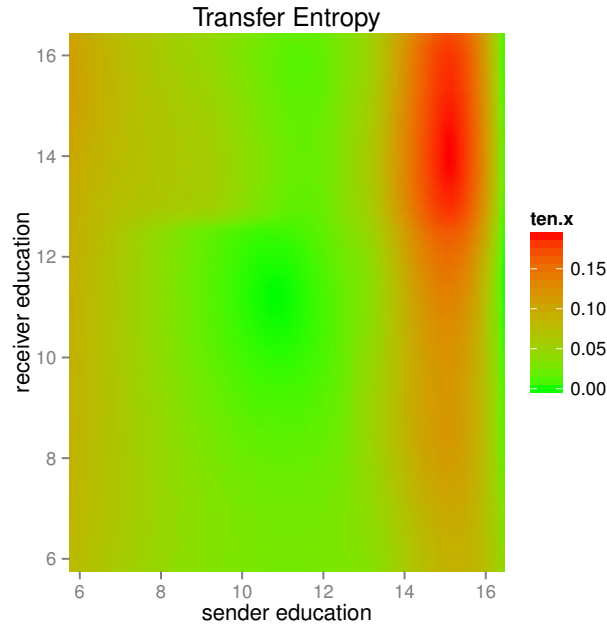


Figure 4.1: Information transfer between social groups with different educational background (x-Axis: sender education; y-Axis: receiver education; green: low information transfer; red: high information transfer).

smoothing) (Cleveland et al., 1992) are used to fit the estimated transfer entropy values to a polynomial surface of degree two determined by sociodemographic characteristics as education, income or age. The above described procedure allows to generate continuous heat-maps (also called elevation maps) as in the Figures 4.1, 4.2 and 4.3 which in this context capture the information transmission between social groups of different educational background, different income and different age. The x-axis displays the years of schooling / income / age of the sending individual (cohort) and the y-axis the educational background / income / age of the receiving individual (cohort). Darker shades of red represent a higher degree of information transmission from  $x$  to  $y$ . In regions with a lighter green shade in contrast the information transmission from the  $x$ -axis to the  $y$ -axis is lower. Figure 4.1 suggests that there is a high degree of information transfer from groups with high education to both groups with lower and higher education. This means that agents with high education are not only net senders of information as was already evident by Table 4.2 but are influential beyond their social class. It is however noteworthy that this influence is not equal on all social groups. The dark red shades in the upper right corner suggest some kind of peer effect: Agents with high education predominantly interact with highly educated peers. The degree of information transmission is accordingly higher within this group.

Figure 4.2 supports the findings of the last section. Social influence here in the

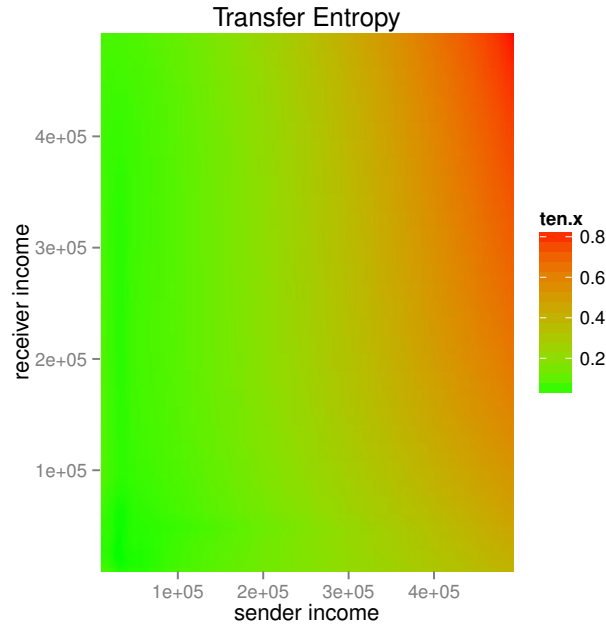


Figure 4.2: Information transfer between social groups with different income (x-Axis: sender income; y-Axis: receiver income; green: low information transfer; red: high information transfer)

context of expectations with regard to the overall economic development is increasing with income. Two things are worthwhile to note: First, as far as high income groups are concerned there also seems to be a peer effect mechanism at work as it is the case for education which was discussed above. Second, agents with low income are susceptible to adopt opinions from other social groups. Figure 4.3 finally breaks down the transmission of information by the age of agents. As was already seen in the last section the most influential agents are between forty and sixty years old. The social influence of this group is not only limited to peers but extends to all age groups. The results presented above give a good notion which factors are determining for the degree of social influence. It has to be noted however, that the above used approach is not suited to investigate sub-group effects of variables like education, age or income separately. In reality there is of course a high coincidence between these characteristics: agents with a higher age tend to have a higher income, agents with higher income tend to have a higher education etc..

#### 4.4.3 Transfer Entropy and Social Networks

A striking feature of applying information theory to survey data as outlined in sections 4.2 and 4.3 is that it not only allows to measure information transmission between different social groups (some results were presented above) but also to take a closer look



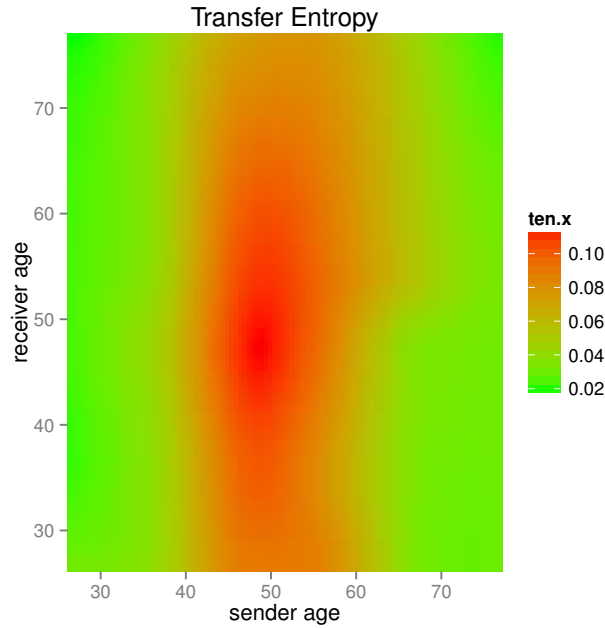


Figure 4.3: Information transfer between social groups with different age (x-Axis: sender age; y-Axis: receiver age; green: low information transfer; red: high information transfer)

at the structure of the underlying network of social influence itself. To do so it is simply assumed that one cohort  $x$  has strong ties to another cohort  $y$  if the sum of transfer entropies in both directions ( $T_{xy} + T_{yx}$ ) surpasses a certain value. In this context we do so by only looking at the highest twenty percent of mutual information flows. Only then it is assumed that there is a close and stable connection between two agents/cohorts. The result is graphically displayed in Figure 4.4. It is striking that there seems to be a hierarchy between the different vertices (of which each represents a cohort)<sup>8</sup>: Thus there are some vertices with a lot of connections while others only have few. Calculating the degree distribution, this means the cumulative frequencies or probabilities of vertices with a given degree (number of ties or links) we can investigate the structure of the network. E.g. the  $P(d)$  is the fraction of vertices with a degree  $d$ . When  $n$  is the number of vertices and  $P(n) = 1$  as well as  $P(d \neq n) = 0$  then one speaks of a *regular network*. In reality networks however rather follow a *power-law*. This means the probability of vertices with higher degrees falls exponentially as the number of degrees increases. In this case such a network is denoted as a *scale-free network*:  $P(d) = cd^{-\gamma}$ . Here  $c > 0$  is a scalar and  $\gamma$  is the exponent of the power law (Jackson, 2008, p. 31).

To test if the social network we established by measuring transfer entropies between each pair of cohorts within the Michigan consumer survey also follows a scale free dis-

<sup>8</sup>Some cohorts dropped out due to the lack of strong connections.

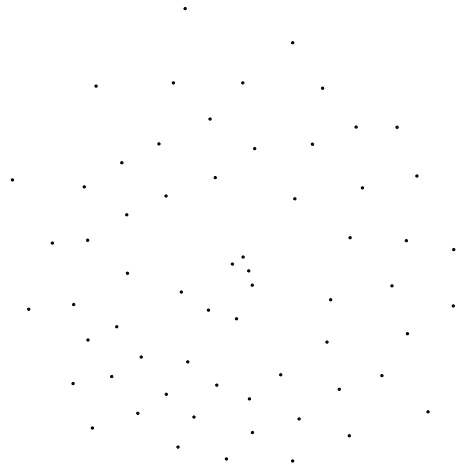


Figure 4.4: The network of social influence as estimated by the University of Michigan consumer Survey

tribution we can simply fit a power-law to the empirical degree distribution.<sup>9</sup> The result is displayed in Figure 4.5. The estimated value of  $\gamma$  corresponds to 2.3643 . A Kolmogorov-Smirnov test with a test statistic of 0.0765 (p-value: 0.9591 ) suggests that the hypothesis that the original sample data from the network established by measuring transfer entropies between pairs of cohorts within the Michigan Consumer Survey could have been drawn from the fitted power-law distribution cannot be rejected. It follows that the estimated network follows a power-law distribution and thus represents a scale free network. The network inferred by the technique outlined above further exhibits a high degree of clustering: The cluster or transitivity coefficient (Wasserman and Faust, 1994) is at 0.3426 reflecting a rather high probability that the neighboring vertices of a node are connected as well.

#### 4.4.4 Higher connectivity, more influence

With regard to the results presented in Section 4.4.2 one might ask if the influence of certain agents on others is also reflected in their connectivity, namely in the degree of the most influential vertices. The transfer entropy alone only measures the information flow from one agent to another. This means the figures presented until now could have depended on a few very strong connections. Displaying Figure 4.4 in the form of *arcplots*

<sup>9</sup>This was done using the *power.law.fit* function implemented in the R package “*igraph*” (Newman,



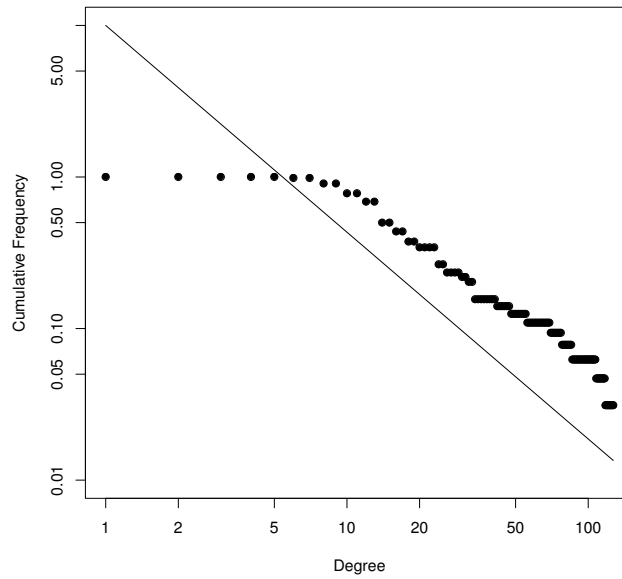


Figure 4.5: Cumulative degree distribution with power law fitted (log-scale)

as done in Figure 4.6 has the advantage that one can order the vertices by certain characteristics which in turn allows to make assertions about how the characteristics influence the connectivity of the vertices. Figure 4.6 shows that the influence of agents indeed coincides with very high connectivity: This means the higher the education or the income of agents the better connected they are. The same is true for higher age. The latter assertion might seem contradictory to the results discussed in section 4.4.2. One has to note however that Figure 4.6 only displays the strongest 20% of connections. Weaker connections were dropped. Therefore not the whole range of age classes (for example those weaker connected age classes beyond 60 years) are displayed in the plot.

This assessment is further supported when taking a closer look at various centrality measures for individual vertices. Figure 4.7 displays four centrality measures as a function of age, education and income:

1. *Degree centrality*: Degree centrality measures the connectedness of a vertex. In a network with  $n$  vertices a vertex can have at maximum a degree of  $n - 1$  (i.e. links to other nodes). The degree centrality measure is then the relation of the degree of one node  $i$  to the number of all other nodes:  $Ce_i^d = d_i(g)/(n - 1)$ . This means the higher the centrality of one vertex with respect to its degree is, the closer to one this centrality measure will be.
2. *Closeness centrality* (Freeman, 1979): This centrality measure is defined as the

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2005; Clauset et al., 2009).



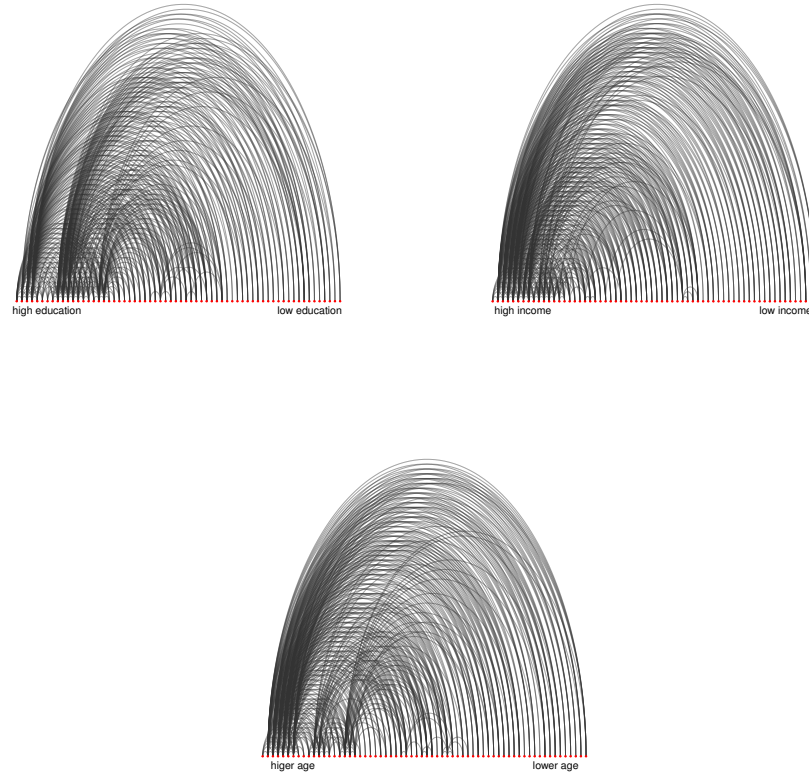


Figure 4.6: The Social Network in the form of ordered arcplots

inverse of the average shortest distance from one vertex to all other vertices. Thus if  $l(i, j)$  is the number of links on the shortest path between the vertices  $i$  and  $j$ , the average distance (number of links) is  $d(i, j) = \sum_{i \neq j} l(i, j) / (n - 1)$  and the closeness centrality measure is  $Ce_i^c = (n - 1) / \sum_{i \neq j} l(i, j) = \sum_{i \neq j} 1 / d(i, j)$ .

3. *Betweenness centrality* (Freeman, 1979): In contrast to the degree and closeness centrality the betweenness centrality doesn't measure the centrality of a vertex by the connectedness of a vertex but rather by its role as an intermediary. The betweenness centrality of a vertex  $i$  is thus the number of shortest paths between a pair of vertices  $j$  and  $k$  on which one can find vertex  $i$  relative to the number of all shortest paths between  $j$  and  $k$  summed over all pairs of vertices. If  $p_{jk}$  is the total number of paths between two vertices  $j$  and  $k$  and  $p_{jk}(i)$  is the number of paths between these two vertices passing through vertex  $i$ , betweenness centrality is defined as:  $Ce_i^b = \sum_{i \neq j \neq k} p_{jk}(i) / p_{jk}$ .
4. *Eigenvector centrality* (Bonacich, 1987): This measure considers not only the con-



nectedness of a vertex but also the connectedness of its neighbors. The centrality therefore not only depends on the links a vertex has but also on how central its neighbors are within the network. If  $A$  is the adjacency matrix of the network  $N$  where its elements  $a_{i,j} \in \{0,1\}$  indicate the presence of a link (0 no link; 1 link) between two vertices  $i$  and  $j$ , and  $M(i)$  is the set of neighbors of vertex  $i$ , the eigenvector centrality of a vertex is the sum of the centralities of its neighbors multiplied by a constant  $\frac{1}{\lambda}$ :  $C_i^e = \frac{1}{\lambda} \sum_{j \in M(i)} C_j^e = \frac{1}{\lambda} \sum_{i \in N} a_{i,j} C_j^e$ . Rearranged in matrix form one gets the eigenvector equation  $Ax = \lambda x$  which is eponymous for this centrality measure.

The different centrality measures formally outlined above capture different notions of centrality. Degree centrality is the simplest concept, reflecting the number of links of a node or vertex. In a directed network, this means if the assumption is made that the edges between vertices are directed, one can further differentiate between the out- or in-degree, i.e. the number of links departing from or arriving at a node. In the context of this study only the overall degree, thus the sum of in- and out-degrees of a node is considered. As outlined above closeness centrality corresponds to the sum of all shortest paths from a specific node to all other nodes. This sum is the lower the more central a node is. Closeness centrality is considered a measure which reflects the importance of an agent spreading information or in other contexts, a disease. Betweenness centrality in contrast measures the importance of a node as an intermediary. It thus measures how many times a node appears on the shortest paths between all other nodes and to what extent a specific node is in control of the communication between other nodes. Eigenvector centrality corresponds to the eigenvalues of nodes in the adjacency matrix. It thus reflects the centrality of a node in relation to the centrality of other nodes to which it is linked. The score of a specific node is the higher, the higher the score of connected nodes is. The Eigenvector centrality thus represents a reciprocal measure of connectedness. (Tanaka et al., 2013; Borgatti, 2005).

The curves in Figure 4.7 were generated by calculating the various centrality measures discussed above for each vertex and interpolating these values with respect to age, education and income using local regressions (Cleveland et al., 1992). The results support the conclusion from above: As far as age is concerned the centrality of an agent within a network of social influence around the age of fifty. The centrality of an agent also increases with income and is the highest at a yearly income of around USD 30,000. The interpretation is however not that conclusive when looking at the graphs displaying the centrality measures as a function of schooling years. Similar to Figure 4.1 the social influence and therefore the centralities of vertices reach their climax between fourteen and sixteen years of education. The centrality measures are however nearly as high for groups with lower education, a phenomenon potentially explicable by a majority effect which appears despite of correcting for survey and cohort weights.



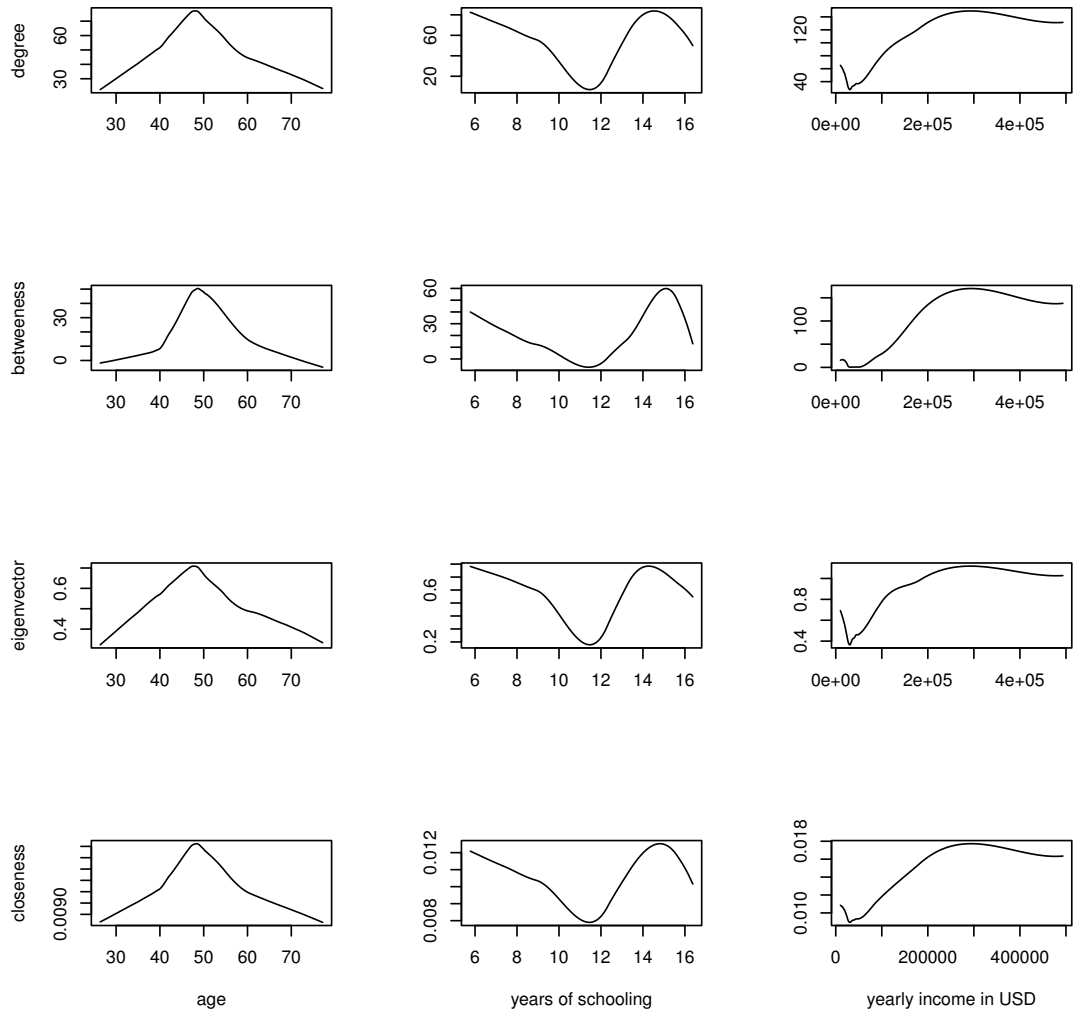


Figure 4.7: Degree, betweenness, eigenvector, closeness centrality as a function of age, education and yearly income in USD

#### 4.4.5 Information transfer over time

Figure 4.8 displays the measured transfer entropies with respect to education, age and income as a function of time. In contrast to before here the width of the time bin  $k$  (outlined in section 4.2) which used to be one month for the results presented above is now varied between one and twelve months. This means while we before only paid attention to the contributions in terms of predictability from  $y_t$  to  $x_{t+1}$  that is  $H(x_{t+1}|x_t) - H(x_{t+1}|x_t, y_t)$  we now instead extend the signal length and look at  $H(x_{t+1}|x_t^k) - H(x_{t+1}|x_t^k, y_t^k)$  where  $x_t^k = x_t, \dots, x_{t-k+1}$ ,  $y_t^k = y_t, \dots, y_{t-k+1}$  and  $k \in 1, \dots, 12$ .

Extending the signal length into the past shows that the information transfer on average sharply increases until  $k = 3$  and slowly decreases for higher bin widths. As already seen in Figures 4.1 to 4.3 influence increases with education as well as income. As far as age is concerned one observes a clear peak at age groups between forty and sixty years. The decline of the transfer entropies when extending the signal length beyond  $k = 3$  is approximately equivalent over all groups.

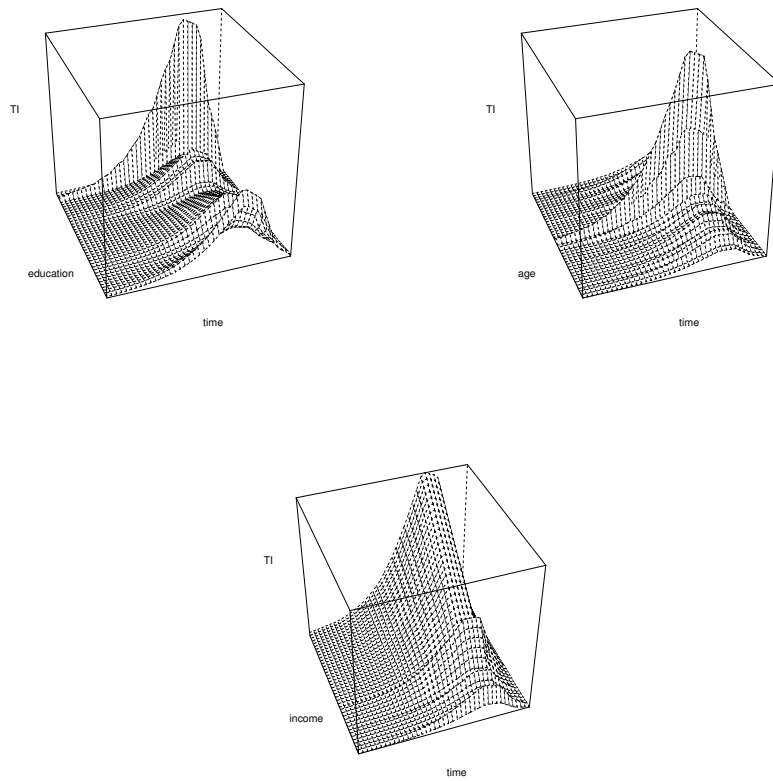


Figure 4.8: Information Transfer under consideration of different time lags

## 4.5 Conclusion

This paper presents a way to apply information theory namely the concept of *transfer entropy* by Schreiber (2000) to consumer surveys. Using self-organizing Kohonen maps the repeated cross-section structure of the University of Michigan consumer survey data set was transformed into a pseudo-panel with 64 cells. Subsequently the information theoretic measure of transfer entropy was used to measure the mutual (i.e. in both directions) information flow between all pairs of cohorts in the context of business expectations. It was shown that social influence is strongly determined by the sociodemographic situation of an agent: Social influence on other agents increases with education and income. As far as age is concerned agents between forty and sixty years are the opinion leaders exerting influence on other groups.

Looking only at the strongest ties in terms of mutual information transfer between the different cohorts within the University of Michigan survey data set allows to assess the underlying network structure. It turns out that the inferred network of social influence is scale-free and follows a power-law with an exponent  $\gamma$  of 2.3643. This means the number of agents falls exponentially with the number of their degrees. Such a network structure is realistic and often observed in other contexts. We further saw that high influence coincides with high connectivity. This means that highly influential agents exert their influence not only on a few other cohorts but play a central role within the network structure. This conclusion can also be drawn when plotting measures as degree, betweenness, closeness and eigenvector centralities against variables as age, education or income: The high degree of social influence by certain groups strongly relies on their central positions within the network of social influence. These respective groups are not only generally well connected but also play important roles as intermediators and are parts of influential cliques. It is further shown that social influence reaches its peak at a bin width of three months of past data but diminishes beyond this point.





## Chapter 5

# A Concept for Constructing an Economic Sentiment Indicator via Web Mining

### 5.1 Objective

Economic Sentiment Indicators have developed into helpful supplementary tools to surveil, analyze and forecast aggregate economic fluctuations in the short run. Traditionally they base on surveys evaluating opinions and expectations of economic agents regarding economic prospects or perceptions of past economic evolutions on a regular basis. Under the assumption that the internet nowadays serves as a large reservoir for the expression of opinions and expectations, this research project aims to construct an economic sentiment indicator analyzing unstructured textual data which is freely available on the internet making use of modern text and sentiment mining technologies in combination with traditional econometric analysis. The proposed web-based sentiment indicator will be able to deliver more up-to-date sentiment information than the traditional monthly survey based sentiment indicators, which allows to track economic trends as they are emerging.

### 5.2 Background and Context

Beginning with the seminal works of Knight (1921) and Keynes (1936) decision making of economic agents is considered to be shaped by expectations and the assessment of risk reflecting among other things psychological aspects (Carnazza and Parigi, 2002). Basing on these theoretical foundations precursors of modern day Behavioral Economics like George Katona committed themselves to construct and develop instruments measuring attitudes and expectations of economic agents towards the economy. The results of this work emerged in the creation of typically survey based indicators in the early post war period, which focused on consumer and business confidence and established themselves



as important supplements to macroeconomic data in forecasting and evaluating trends in the evolution of the economy (Katona, 1974). Early and well known proponents of indicators directed at households are e.g. the University of Michigan Consumer Sentiment Index (MCSI)<sup>1</sup>, conceptualized by George Katona and regularly updated since 1955, or the Consumer Confidence Index (CCI), which started in 1967 and is since then updated and maintained by the U.S. Conference Board. Later on the concept of survey based assessment of economic sentiment was extended to businesses as in the form of the Philadelphia Fed Index, which is conducted since 1968, or the German IFO Business Climate index, which has its roots in the late 1940s and is regularly measured and published since 1972. Similar approaches to assess economic sentiment are nowadays applied in all major economies. Partly sentiment indicators are bundled or enriched with macro-data to allow for a better evaluation of future economic prospects. An example for such a composite index, which combines the survey results from different industries and countries, is the European Economic Sentiment Indicator (ESI) directed by the European Commission. A special form of sentiment indices represent the surveys of professional forecasters, as e.g. the Philadelphia Fed's Survey of Professional Forecasters, concerning the evolution of macroeconomic variables.

All aforementioned indices have in common that they use a survey design to evaluate the assessment of economic prospects with respect to the current economic situation. Households e.g. might be asked how they expect their income to change within a certain period in comparison to the moment of the survey. Businesses might be surveyed how they judge their inventory holdings or how they expect their order books to evolve. The respondent is however not asked to give precise quantitative answers but rather to choose one out of different qualitative and ordered answering options, e.g. did the order situation improve, stay the same, did it get worse. In the simplest case the so gained qualitative results are converted into quantitative, aggregate sentiment data by setting the proportions of optimistic and pessimistic answers into relation. Fluctuations around the scaled long term average can then be used to make assertions over the confidence of households or businesses (Carlson and Parkin, 1975; Pesaran, 1984)<sup>2</sup>. The qualitative, expectation and opinion focused design of the above mentioned indices stands in contrast to a second category of indices which asks for factual information rather than expectations or opinions. As an example for this group the numerous Purchasing Manager Indices can be mentioned (Pesaran and Weale, 2006b).

Consumer sentiment and business sentiment indicators enjoy, due to their good predictive properties and their function as leading indicators for macro-data, which can only be measured in bigger time intervals, great popularity among business cycle researchers and professionals in the financial industry. Various empirical studies prove this features, e.g.: Mourougane and Roma (2003) study the predictive power of the ESI for the short term real GDP growth in different European economies. Ludvigson (2004) shows that consumer sentiment is a good predictor for consumer spending. Howrey (2001) demonstrates that consumer sentiment captured by the MCSI can serve as a good predictor

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<sup>1</sup>Data from the MCSI was used in Chapters 3 and 4)

<sup>2</sup>More sophisticated quantification results were discussed and applied in Chapters 2 and 3.



for real GDP growth. Vuchelen (2004) follows a similar approach and comes to analog results in the Belgium context. Grisse (2009) studies the feedback effect which can eventually arise by publishing business confidence indices, rendering the so measured expectations to be self-fulfilling prophecies of economic prospects.

### 5.3 Significance of the Study

The spread and development of internet technologies as well as the increased user-friendliness of web applications in the recent years has transformed the web from a tool which initially served mainly the passive consumption of information into a vehicle to share opinions with others and to participate in the discourse about every thinkable issue. The web 2.0, as it is referred to occasionally in media, allows users without further technological knowledge to interactively exchange information and in this sense also to utter mood and sentiment, be it in blogs, reviews or newsgroup messages. It seems therefore reasonable to fathom the potential of sentiment information stored in unstructured textual information on the web to study expectation formation in the context of business cycle research and to forecast economic trends.

The above described evolution of web technologies and the change of their employment lead computer scientists, mainly motivated by the economic interest of businesses, to develop technologies to systematically analyze, classify and quantify the vast, ever increasing amount of mainly textual and therefore unstructured information. The combination of traditional linguistic methods of text analysis with improving capacities regarding software, processing power, the further development of machine learning algorithms as well as the availability of training corpora<sup>3</sup> contributed crucially to the enormous progress in this respect and culminated into the very active research field of sentiment or opinion mining respectively. The employment of these techniques allows businesses to semi-automatically evaluate costumer reviews, feedback and opinions in order to more efficiently account for their preferences in the context of reputation management or to compile forecasts concerning trends in order to enhance their chances in the market (Mishne and Glance, 2006; Lee, 2004). Policymakers take advantages of opinion mining technologies to evaluate public opinion considering pending law or regulation proposals. This subfield is denoted as “*eRulemaking*” (Cardie et al., 2006; Kwon et al., 2006).

The applications of these techniques in an economic context are yet relatively rare though quite promising. The only works to which in the broader sense a principle similarity can be attributed to the approach envisaged for this project, are those by Tims et al. (1989), Blood and Phillips (1995), Fan and Cook (2003) as well as Doms and Morin (2004). Above mentioned articles find that economic news coverage has

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<sup>3</sup>A Corpus denotes a structured set of texts which e.g. can be used to experiment with machine learning algorithms to automatically classify texts by topic or polarity (sentiment). A well known training corpus is the Reuters RCV1 corpus distributed by the National Institute of Standards and Technology which contains several hundred thousands newswire articles published by the news agency Reuters to which meta informations as e.g. place and subjects were attributed by hand.



significant influence on consumer sentiment. Doms and Morin (2004) for example show that the appearance of negatively connotated expressions like *recession* and *slowdown* in news coverage about economic topics has significant explanatory power for decreases in consumer confidence. Starr (2012) confirms the coherence of consumer sentiment and news coverage using surveys in the context of the data collection for the Michigan Survey of Consumer Attitudes. This empirical literature indirectly references the idea of the theoretical literature on *Pigou-Cycles* which explains the cyclical movement of the economy by positive *news shocks*, leading to economic boom phases which result into a *bust* when it turns out that expectations were too optimistic. These ideas, originally developed by Arthur Pigou (1929) in the 1920s, recently experienced a renaissance in literature as there is evidence to suggest that similar mechanisms played a role in the emergence and bust of the dot-com bubble in the 1990s where markets overestimated the potential of new internet technologies (Beaudry and Portier, 2004; Collard, 1983; Beaudry and Portier, 2006; Jaimovich and Rebelo, 2009). The high degree of optimism in this time is also reflected in the consumer sentiment and business confidence data of this period (Mehkari, 2010). The above cited works however don't take advantage of the computerized sentiment mining techniques which are envisaged for this project, but rather come to their results through manual data collection and traditional quantitative methods. They nevertheless indicate the following points, which are central assumptions for the here presented research project: First, textual information can be a carrier for economic sentiment. Second, a less trivial conclusion, the impact of this sentiment can be measured.

That news and written communication in general have an impact on market expectations can also be shown from another direction, which suggests that computerized text mining could be an appropriate tool for the detection of economic sentiment but also illustrates a potential strategy for the project to construct an Economic Sentiment Indicator by analyzing unstructured textual data published on the web. Koppel and Shtrimberg (2006) e.g. suggest a method to automatically categorize news stories into *negative* or *positive polarity* by the impact they have on stock market movements. In their article the authors examine a corpus of 12,000 news articles between the years 2000 and 2002 concerning items within the Standard & Poor 500 (S&P500) stock market index which corresponds to around 24 news stories on each asset. By looking at the stock movements within a certain time frame after publication, the news articles were categorized into groups with negative and positive impact respectively. For the upward (positive) and downward (negative) movements respectively threshold values were chosen to assure that the changes don't simply reflect random fluctuations or normal market movements. Further it was defined that the respective items have to have a minimum value and that the percentage alteration of the prices in question has to exceed the percentage change of the S&P500 index within the same time period. Then binary word frequency vectors were compiled in which irrelevant function words were pruned. Consequentially learning algorithms like Support Vector Machine (SVM), Naïve Bayes and Decision Trees were used to learn the text and word patterns connected with the polarity respectively. A tenfold cross-validation experiment, in which it was tested to



what extent the learned text pattern were applicable to categorize articles, yielded a classification accuracy of around 70% (Koppel and Shtrimberg, 2006). This supports on the one hand the results of the other literature cited above, namely that there is a relevant and significant connection between news and expectations which influence markets, on the other hand the experiment by Koppel and Shtrimberg shows that learning algorithms can be used to recognize sentiment patterns in text which can influence the behavior of economic agents.

Another interesting approach to use text and sentiment mining techniques in context of economic problems comes from Ghose et al. (2007). Ghose et al. (2007) investigate by the application of text mining in combination with econometric methods, if the positive/negative sentiments uttered in costumer reviews on the online market platform [www.amazon.com](http://www.amazon.com) have an effect on the price premium sellers could take, respectively if one could infer a positive/negative polarity of expressed opinion by the pricing power of a seller. Therefore the authors identify dimensions of reputation which are important for the evaluation of the services a seller offers. Such dimensions could be e.g. delivery, packaging, costumer support etc. By the use of a natural language processing algorithm (NLP) parser (this parser is an algorithm to identify parts of speech (POS) as nouns, verbs, adjectives and adverbs and sets them into relation to each other) the authors find modifiers of these dimension. If one for example considers the dimension “*delivery*”, which is the noun along the POS scheme, the adjective “*speedy*” would be a modifier. Parsing out the modifiers for every dimension from the customer reviews regarding a seller yields a dimension/modifier matrix for each merchant. By weighting with respect to dimension and time of the reviews, newer reviews are weighted higher than older reviews, a virtual reputation score for each merchant is calculated. Then after panel OLS-regressions with fixed effects were run where the impact of the independent variable, the reputation scores of two competitors within one market (additionally to that the [www.amazon.com](http://www.amazon.com) star rating system, the number of past transaction and the number of sellers in the market were used as control variables), for the dependent variable, the charged price premium, was estimated. The resulting significant coefficients for several modifier-dimension pairs can then be calculated, with the weightings, and interpreted in monetary terms. The study of Ghose et al. (2007) yields two important results: First, it demonstrates that sentiment and opinion have a measurable condensation in unstructured textual data, second and more importantly, economic agents absorb subjective experiences of others and consider it in their decision making as reflected by the effect of enhanced pricing power for merchants with good reputation.

A commanding impression which potential user generated data on the internet has for economic forecasting, even if to lesser extent connected with the field of sentiment mining, delivers the paper by Schmidt and Vosen (2009). Under the assumption that more and more customers use the internet as a research instrument in preparation of acquisitions, the authors use data provided by the search engine Google in the context of the *Insights for Search* application about search terms entered by users to forecast private consumption. It is shown that both with and without combination of other macro-data the *Google-Trends* data exhibits a higher predictive power for private consumption than



traditional, survey based consumer sentiment indicators as the MCSI and the Conference Board Consumer Confidence Index.

Last but not least the work by Hal Varian has to be mentioned in this context. He was one of the first in the Economic profession to realize which impact web technologies would have for the business life and the field of Economics. Noteworthy in this regard is his famous book “*Information rules: a strategic guide to the network economy*” (Varian and Shapiro, 1999) coauthored with Carl Shapiro. Currently holding the position of Googles chief economist he is one of the most visible proponents of combining web technologies and data mining with traditional econometric methods. Especially his work together with Choi received significant attention, in which the authors demonstrate, similar to the above cited article by Schmidt and Vosen (2009), the impressive properties of Google Trend data to forecast inter alia automobile sales, unemployment claims and consumer confidence (Choi and Varian, 2012). In his article “*Big data: New tricks for econometrics*” Varian gives an overview of applications of machine learning to big data in an economic context (Varian, 2014). Of special interest for econometricians is thereby his discussion of Bayesian Structural Time Series analysis with feature selection, which is used to choose the best predictors for home sales figures from a wide variety of Google query time series data. The initial set of predictors was hereby chosen using the Google Correlate tool, which allows to submit a time series and returns hundred queries which, in terms of search frequencies, have the highest correlation with the originally uploaded time series. Likewise appealing is his outline of model averaging, a method widely used in machine learning but relatively new to Econometrics, to enhance prediction quality. Varian however also points out a weakness of machine learning techniques for the application in Economics: Algorithms like random forests can be extremely complex and thus very difficult to interpret (Varian, 2014, p. 15). A good overview of recent applications of machine learning techniques in Economics is given by Einav and Levin (2013).

This section sketched the potential of using computerized sentiment mining for economic sentiment analysis: With reference to examples from literature it was shown that text mining technologies applied on unstructured textual data have the ability to parse out sentiments which can be set into an economic context, meaning that the impact on economic behavior of analyzed sentiment can be measured and is significant. The use in economic problem fields, especially on an aggregate level, is however rare or inexistent respectively. The next section is dedicated to outline a strategy how an economic sentiment indicator measuring consumer and business confidence following the example of survey based indicators can be constructed using computerized sentiment mining techniques on unstructured textual data published on the internet.

## 5.4 Methodology

The principle procedure to construct a web based economic sentiment indicator is as follows: Given a sufficiently large training corpus with documents which are annotated with regard to topics and sentiment, text mining techniques can be used to make these



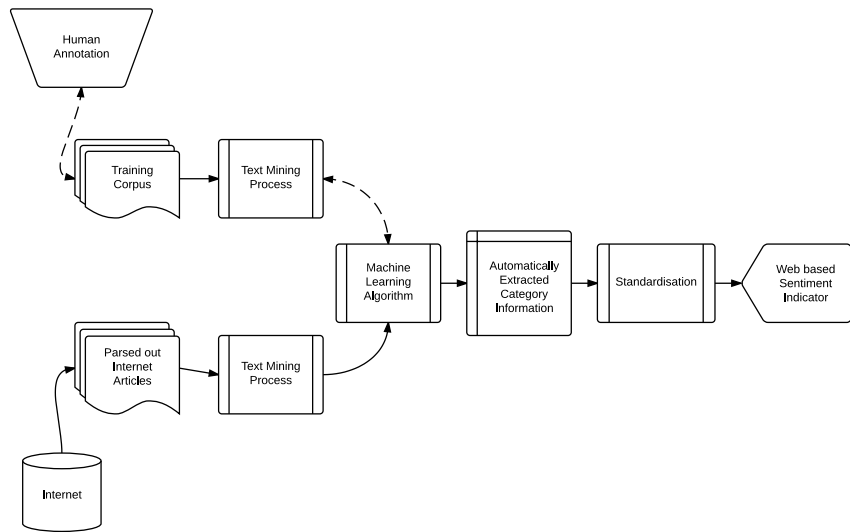


Figure 5.1: Flowchart of the Procedure

documents machine readable. With the annotated training corpus and the use of machine learning algorithms the computer can be taught to recognize the specific patterns characterizing for textual documents and to automatically categorize new texts, which were parsed out from the web, along the predefined annotation schemes e.g. topics and sentiment. This results into time- and topic-referenced sentiment information, similar to the sentiment information extracted by surveys, which can be used to construct a sentiment indicator reflecting economic confidence and trends. In the following the steps and elements necessary to construct a web-based economic sentiment indicator based on analyzing textual information on the internet via text mining will be described in more detail. The procedure is schematically displayed with a flowchart in Figure 5.1.

#### 5.4.1 Data Sources and Collection

The sources which can be potentially used for the construction of a web based Economic Sentiment Indicator as envisaged here are manifold as there is a huge, ever increasing amount of textual data available on the internet. Two points are however crucial: First, the examined articles have to have a time stamp. This means the date and time when the article was published must be known and parsable. Second, the originality of the article must be assured. This means it would for example make no sense to read out news information of several english speaking online newspapers about a certain topic knowing that they are most probably just copied versions of articles bought from press agencies as e.g. Reuters. Considerable information sources would therefore be newswire articles from press agencies directly, blogs, news group articles or even short message services. It might also be interesting to take a look at so called news crawlers or news feeds as

sources. These are websites and applications respectively which parse out articles from different websites about certain topics. The probably most comprehensive newsfeed is the news feed provided by google.com. The advantage of news feeds is that they deliver textual content already in categorized form. Important to mention is however that the project foremost concentrates on resources from the English speaking world: First, because there is a by far greater variety of text mining algorithms for the English language than for any other language, second but not least, because the publication will be in English. The same methods though can of course be broadened to any other language.

For the purpose of experimentation and training of the envisaged model there are several training corpora available. This facilitates the project insofar as for the calibration and testing of the model no data has to be retrieved from the internet which can be time and resource consuming. The most appropriated corpora for the here envisioned purpose seem to be the Reuters RCV1, this corpus contains 810,000 newswire articles from Reuters between 1996 and 1997 and is distributed by the National Institute of Standards and Technology (Lewis et al., 2004), and the TREC BLOG06 test collection, which is a corpus of several million blog documents and news feeds from 2005 to 2006 collected and distributed by the University of Glasgow (Ounis et al., 2008). Advantageous features of the RCV1 corpus are e.g. that it is freely available and that documents are in the hierarchic XML language which makes it easy to parse out necessary and useful information as publication time, places and topics. These are the reasons why the RCV1 corpus was used in the experimental crowd sourcing platform which was set up to create an annotated training corpus and will be presented later on.

There are however many other suitable corpora. Noteworthy are for example the New York Times Annotated Corpus, which contains 1.8 million New York Times articles published between 1987 and 2007 (Sandhaus, 2008). A huge advantage of this collection (like with the RCV1 corpus) is, as will be clearer later on, that the articles were annotated by humans. This means every article contains labels and tags regarding topics and places, etc., which were systematically attributed by the NYT staff.

### 5.4.2 Text mining

Text mining in its basic sense is an umbrella term for computer linguistic methods to systematically organize weakly structured textual information in a way that it is open to numerical statistical analysis and readable for machines. All further on described tasks are standard applications in available text mining software packages. Taken that a collection of documents, a corpus, should be analyzed, a text mining project normally begins with splitting up the individual texts into words denominated as tokens. This process is named *tokenization* and ultimately pursues the objective to compile a term frequency matrix which makes the corpus readable for machines and allows the automatized comparison and analysis of different documents in the corpus. A term frequency matrix indicates if or how often a certain parsed out term, a token, occurs in a certain document within a corpus. A corpus containing  $n$  documents and overall  $m$  tokens would therefore result in a  $n \times m$  term frequency matrix (see for example Table 5.1). The above



	word 1	word 2	word 3	...	word $m$	label
document 1	0	1	1	...	1	.
document 2	1	0	0	...	0	.
document 3	0	0	1	...	0	.
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
document $n$	1	0	1	...	1	.

Table 5.1: Example of a binary term matrix

described procedure alone would however result into a huge data set, which not least due to redundancies yields just marginal gains of information.: If for example a corpus of English documents is big enough, it is reasonable to assume that a term frequency matrix would have to capture a sizable fraction of the vocabulary of the English language. Due to inflections, declension and conjugations, it would additionally contain several forms of the same word. Because of all this, tokenization is usually followed by a row of other procedures to reduce data amount drastically. These procedures involve filtering, pruning and stemming algorithms. One might for example want to filter out stop-words as “*the*”, “*this*” or “*an*” which are regarded to have no informational content. Additionally tokens are also filtered or pruned by their frequency, be it in absolute or fractional terms, since this could bias the results gained by the application of machine learning procedures (to be discussed later on): One could for example easily come to the conclusion that the appearance of the very frequent token “*be*” is not a very distinctive feature for an English text document. Tokens which appear on the other hand very seldom, like names, might also yield no informational gain. Another filtering method is e.g. the lexical substitution of synonyms to avoid redundancies. The most complex procedure of data reduction is however stemming. Stemming intends to reduce the parsed out tokens to their morphological roots. Instead of capturing for example both words “*fisher*” and “*fishing*” in a term frequency matrix, one would prefer to measure only the occurrence of there common root “*fish*”. There are two main types of stemming algorithms: Brute force or lexical algorithms on the one hand use lookup tables to substitute tokens by their respective morphological roots. Suffix-stripping algorithms on the other hand use inflection rules to cut suffixes from words, e.g. the word “*gone*” would appear by it’s root “*go*” in the term frequency table. Brute force algorithm are regarded as more precise especially as they have hardly problems with irregular inflections. They are however very complex to maintain and resource consuming in their application. In contrast to that, suffix-strippers are quite efficient with the downside that they have problems with irregularities. For most of the tasks in the context of machine learning and text similarities as relevant for the here envisaged project their capacities are however sufficient. One well known and widely applied algorithm of this type is the Snowball-Stemmer (Porter, 2001; Weiss et al., 2005).

Having conducted the above described preparatory procedures (which procedures are applied to which extent of course depends on the research interest) a term frequency matrix can be compiled. This renders the unstructured textual information readable for

machines. *Machine learning algorithms*, these algorithms will be discussed in the next section, can then be applied in order to detect patterns and conduct automatized categorization. Table 5.1 displays an exemplary term-frequency matrix with binary values. Other forms of term-frequency matrices display the absolute numerical occurrence of a term. In a third variant the *term frequency - inverse document frequency*, the so-called *TF-IDF* score, is calculated. This means that terms are counted but down-weighted if they appear in many documents and up-weighted if they appear relatively seldom.<sup>4</sup> Other concepts of term frequency tables count *n-grams*, which are sequences of *n* tokens, instead of terms, which are considered to be *uni-grams* along this approach. For more specified categorization purposes *part of speech* tagging in combination with simple tokenization can be considered. Most of the major text mining software applications are able to recognize the role of a word within a sentence. This means they can distinguish if parsed out tokens are e.g. nouns, verbs, adjectives, etc.. If one wants e.g. to categorize documents with regard to the topics they are covering, one might find it more appropriate to apply machine learning algorithms on nouns only since the occurrence of verbs is less context dependent. Allowing for all parts of speech in a text categorization procedure can lead to a lower accuracy. This phenomenon is denoted as “*over-fitting*”. (Masuyama and Nakagawa, 2004; Weiss et al., 2005)

### 5.4.3 Machine Learning Algorithms

Machine Learning algorithms are the core of every sentiment mining project. They have the ability to recognize patterns and categorize documents into preset categories, be it topics, places or polarities (sentiments). The issue of machine learning algorithms was already briefly touched in the sections above where the potential of text mining for economic sentiment analysis was discussed. The principle of the four most popular machine learning approaches, *support vector machines* (SVM), *Naïve Bayes*, *decision tree classifiers* and *Artificial Neural Networks* shall be shortly addressed in the section that follows.

**Support Vector Machine** The most widely applied machine learning algorithm is the *support vector machine* (SVM) approach. Its concept is depicted in Figure 5.2. The goal of the SVM in the linear case is to find a hyperplane, which efficiently separates the positive sample from the negative sample, depicted by the black and white dots respectively. Such a separation rule can then be used to categorize yet unlabeled samples. Given a set of training data  $\mathcal{D} = \{(x_i, y_i) | x_i \in \mathbb{R}^d, y_i \in \{-1, 1\}\}_{i=1}^n$  with  $i = 1, \dots, n$ , where the label  $y_i \in \{-1, 1\}$  describes to which category the *d*-dimensional vector  $x_i$  belongs, the SVM calculates the optimal hyperplane  $w \cdot x - b = 0$  which delivers the maximum margin to the positive and negative sample respectively. The margins are defined to be the distances  $d_+$  ( $d_-$ ) from the optimal hyperplane to the closest point of the positive (negative) sample.  $w$  is normal to the hyperplane, and  $b/\|w\|$  with  $\|w\|$ ,

<sup>4</sup>If  $tf(j)$  is the overall frequency of term  $j$  in  $N$  documents, and  $df(j)$  gives the number of documents in which the term  $j$  appears, then  $tf-idf(j) = tf(j) \log(\frac{N}{df(j)})$ .



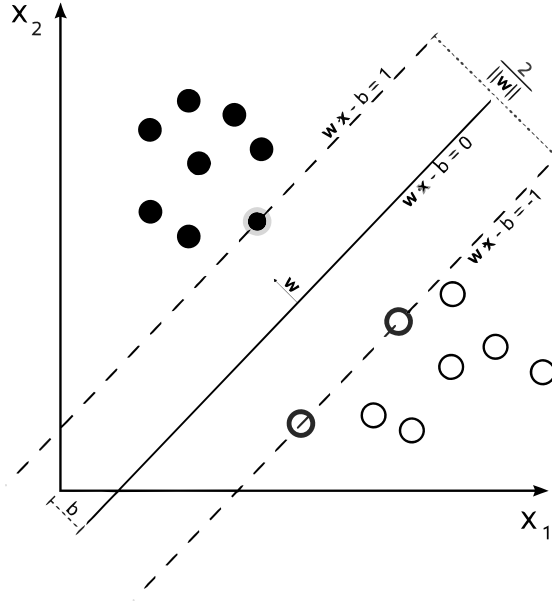


Figure 5.2: Principle of SVM

the Euclidean norm of  $w$ , describes the perpendicular distance from the hyperplane to the origin. The SVM now sets  $w$  and  $b$  in order to maximize the overall margin  $d_+ + d_-$ . Differently put, the SVM maximizes the distance between the parallel hyperplanes  $w \cdot x_i - b = 1$  and  $w \cdot x_i - b = -1$ , denoted as the “*support vectors*”, which are still barely separating the two samples. The distance between these two “*support vectors*” is  $\frac{2}{\|w\|}$ . The task is therefore to minimize  $\|w\|$ . Since it is clearly not desirable that points are falling into the margin one can redefine the “*support vectors*” to  $w \cdot x_i - b \geq 1$  and  $w \cdot x_i - b \leq -1$  respectively, which in combination can be rewritten to the constraint  $y_i(w \cdot x_i - b) \geq 1$ . The problem can then be written down as a quadratic programming problem  $\min_{w,b} \|w\| \quad s.t. \quad y_i(w \cdot x_i - b) \geq 1 \quad \forall i = 1, \dots, n$  or, for the sake of convenience but without altering the result, as  $\min_{w,b} \frac{1}{2} \|w\|^2 \quad s.t. \quad y_i(w \cdot x_i - b) \geq 1 \quad \forall i = 1, \dots, n$  ( $\|w\|$  is the norm of  $w$  and thus contains a square root, which is hard to minimize). By introducing a positive Lagrange multiplier  $\alpha_i$  for  $i = 1, \dots, n$ , the problem can be denoted in an easier to handle Lagrangian formulation:

$$\mathcal{L} = \min_{w,b} \max_a \left\{ \frac{1}{2} \|w\|^2 - \sum_{i=1}^n \alpha_i [y_i(w \cdot x_i - b) - 1] \right\}$$

Since the sub condition is set to equality, it is thus required that, subject to the constraint  $\alpha_i \geq 0$ ,  $\mathcal{L}$  is minimized with respect to  $w$  and  $b$  while the derivatives of  $\mathcal{L}$  with respect to  $\alpha_i$  have to disappear. It can be shown that the solution  $w$  can be expressed as a linear combination of the training vectors  $x_i$ ,  $w = \sum_{i=1}^n \alpha_i y_i x_i$ . From this and the sub condition of the minimization problem set to equality,  $y_i(w \cdot x_i - b) = 1$ ,  $b$  can be derived

as  $b = w \cdot x_i - y_i$ . Equivalently one can write the optimization problem, using the results from before and the fact that  $\|w\| = w \cdot w$ , as

$$\begin{aligned} \max_{\alpha_i} \mathcal{L} &= \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j x_i^T x_j = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j k(x_i x_j) \\ \text{s.t.} \quad & \\ & \alpha_i \geq 0 \\ & \sum_{i=1}^n \alpha_i y_i = 0 \quad (\text{the constraint minimizing w.r.t. } b \ \forall i = 1, \dots, n) \end{aligned}$$

The function  $k(\cdot)$  is the kernel defined as  $k(x_i, x_j) = x_i \cdot x_j$ . If no hyperplane can be found to separate the samples, a soft margin can be implemented by introducing a slack variable  $\xi_i$  into the classification constraint to allow a certain degree of misclassification:  $y_i(w \cdot x_i - b) \geq 1 - \xi_i \quad \forall \quad i = 1, \dots, n$ . The general procedure stays the same with a slack variable. The slack variable  $\xi_i$  is just an additional variable with respect to which one has to minimize. Non-linear classification problems can be solved by mapping the separation problem into a higher dimensional Euclidean space using alternative kernel functions  $k(\cdot)$ . For multiple classification classes, more than two, one could choose a stepwise procedure by breaking down the problem into several dual classification problems and classifying each class in comparison with all others classes, or by pairwise coupling, namely by classifying each class with respect to each other class. Other approaches, like the Decision Directed Acyclic Graph (DDAG) or the Directed Acyclic Graph SVM (DAGSVM) algorithms, try to combine many standard SVM dual-class classifiers into one algorithm. (Burges, 1998; Taira, 2002; Duan and Keerthi, 2005; Piatt et al., 2000)

**Naïve Bayes** A second type of classifiers is the Naïve Bayes classifiers. Naïve Bayes algorithms are simple, resource saving and though very efficient. They are for example widely used for filtering out spam E-Mails. A Bayes Classifier along Bayes' Theorem is in its purest form a function  $f$  which maps a vector  $X$  of a  $n$ -dimensional feature-space into a set of classes  $Y$ :  $f : X \in \mathbb{R}^n \rightarrow Y$ . It is assumed that  $Y$  is a boolean-valued random variable and that  $X$  is a vector comprising  $n$  boolean features, thus  $X = \{X_1, \dots, X_i, \dots, X_N\}$ . With respect to the here considered text classification one could assume that a document, which is characterized by the possible occurrence of  $n$  different words  $X$ , should be classified into different classes e.g.  $Y \in \{\text{spam}, \text{no-spam}\}$ . Bayes' Theorem states that

$$P(X, Y) = P(X|Y)P(Y) = P(Y|X)P(X)$$

Where  $P(X)$  is the evidence (distribution of features in the  $n$ -dimensional feature space),  $P(Y)$  the *prior probability* for class  $Y$ ,  $P(Y|X)$  the *posterior probability* for  $Y$  with respect to  $X$  and  $P(X|Y)$  the class conditional likelihood. Therefore the *posterior probability* can be expressed by,

$$P(Y|X) = \frac{P(X|Y)P(Y)}{P(X)} = \frac{P(X|Y)P(Y)}{\sum_{Y'} P(X|Y')P(Y')}$$



Since  $P(X) = \sum_{Y'} P(X|Y')P(Y')$  as  $P(X)$  can be regarded as the marginal value of  $P(X|Y)$  with respect to  $Y$ . Thus actually only the numerator of the *posterior probability* formula is of interest. The Bayes classification problem therefore can be denoted as

$$Y^* = \arg \max_Y P(Y|X) = \arg \max_Y \frac{P(X|Y)P(Y)}{P(X)} = \arg \max_Y P(X|Y)P(Y)$$

To ensure the pure Bayes Classifier works efficiently, it has to be trained with a sufficiently big training sample. To stick to the spam-filter example, this means that the user has to tag a sufficiently high number of E-Mails as “*spam*” or “*not spam*”. In the case of the spam-filter one can assume that  $Y$  is a boolean variable and  $X$  exhibits  $n$  boolean attributes (words). This implies that  $X$  can take on  $2^n$  and  $Y$  can take on 2 values. One has to note that by probabilistic rules it has to hold that  $\sum_{X_i} P(X_i|Y) = 1$ . This implies for every value  $Y$  can take, one has to estimate  $2^n - 1$  parameters. If  $Y$  is boolean, as in the spam-filter example, one has to therefore estimate  $2(2^n - 1)$  parameters. To get reliable estimates (frequencies) one has to conduct the estimation procedure several times. Thus under the assumption of  $n = 50$ , rather unrealistic with regard to spam-filters, one would have to tag several billion E-Mails in order to get a reasonably reliable spam-filter. This is where the idea of Naïve Bayes classifiers sets in. The Naïve Bayes classifier, in contrast to the pure Bayes classifier sketched above, makes the *naïve* assumption that features  $X_i$  and  $X_j$  for all  $i \neq j$  are conditionally independent. This implies that  $P(X_i|Y, X_j) = P(X_i|Y) \quad \forall i \neq j$ . Along this assumption the formula for the *posterior probability* can be rewritten: The numerator  $P(X_1, \dots, X_n|Y)P(Y)$  can be simply denoted as the joint probability  $P(Y, X_1, \dots, X_n)$ . Applying the chain rule, the joint probability  $P(Y, X_1, \dots, X_n)$  can be rewritten in the following way:

$$\begin{aligned} &P(Y, X_1, \dots, X_n) \\ &= P(Y) \cdot P(X_1, \dots, X_n|Y) \\ &= P(Y) \cdot P(X_1|Y) \cdot P(X_2, \dots, X_n|Y, X_1) \\ &= P(Y) \cdot P(X_1|Y) \cdot P(X_2|Y, X_1) \cdot P(X_3, \dots, X_n|Y, X_1, X_2) \\ &= P(Y) \cdot P(X_1|Y) \cdot P(X_2|Y, X_1) \cdot P(X_3|Y, X_1, X_2) \cdot P(X_4, \dots, X_n|Y, X_1, X_2, X_3) \\ &\dots \\ &= P(Y) \cdot P(X_1|Y) \cdot P(X_2|Y, X_1) \cdot \dots \cdot P(X_n|Y, X_1, \dots, X_{n-1}) \end{aligned}$$

Taken the assumption of conditional independence from before the joint probability  $P(Y, X_1, \dots, X_n)$  can be rewritten to the form  $P(Y, X_1, \dots, X_n) = P(Y) \prod_i^n P(X_i, Y)$ . This implies that under the assumption of conditional independence one has to only estimate  $2n + 1$  parameters, in contrast to the  $2(2^n - 1)$  parameters from before, which brings an enormous reduction of training requirement and makes it feasible for text mining tasks as e.g. spam-filtering. (Mitchell, 2005)

**Decision Tree Classifier** The third most common type of machine learning classifiers is the *decision tree classifier*. If the categories are discrete, as in the envisaged

construction of an economic sentiment indicator (polarity, topics, places), one speaks of *classification trees*. Classifiers for continuous categories in contrast are denoted as *regression trees*. The principle of classification trees is simple. Assume that a set of training data, which is pre-classified into two categories, is given. Additionally certain statistical features of the set of training data are known from observations. In the context of spam-filters e.g. one knows by observation that a certain word appears with a certain probability in spam or non-spam mails respectively. The goal of the decision tree is to split up the training set into subsets with the highest possible homogeneity in terms of category. Assume that the training data is described by  $n$  features of which their probability distribution with respect to each category is known. Features in the context of decision trees are called *splitters*. The decision tree is categorized by decision nodes. At each node the algorithm chooses the best (binary) splitter, which is the feature that reduces the heterogeneity in terms of categories in the resulting partitions by the highest degree. This process is repeated on the next decision node with the remaining features and so on. The process is conducted stepwise from the root, the first decision node, to the leaves, the terminal decision nodes, where further splitting wouldn't bring any additional decrease of heterogeneity. Applying the so learned decision rules on real world data (e.g. texts parsed out from the web), full grown classification trees often show inefficiencies due to over-fitting. This effect is reduced by algorithmic pruning, which means to cut branches which developed because of random effects in the smaller training data set, that don't appear in the real world (Rokach and Maimon, 2008, 2005). *Decision tree classifiers* are widely used e.g. in medicine for the diagnosis of ailments. This not least the case because they are, in contrast to e.g. the *SVM* or *Naïve Bayes* approach described above, easily comprehensible and interpretable. Applied on big real world data sets they are however, compared to *SVM* or *Naïve Bayes*, statistically slightly inferior. The *random forest* approach for example therefore tries to control for this issue by combining many uncorrelated decision trees (Breiman, 2001).

**Artificial Neural Networks** As a fourth category of machine learning algorithms *Artificial Neural Networks* can be mentioned. The term *Artificial Neural Network* however has to be understood as an umbrella term for a whole class of computational models which can also be used for classification purposes rather than a principal classification method as those described above. *Artificial Neural Networks*, like the name suggests, are in their design inspired by the neuronal construction of the brain.<sup>5</sup> An Artificial Neural Network along this model possesses an *input layer*, synapses, through which informations or signals are weighted and routed to the hidden layer which are mathematical functions, neurons or processing units, which, if activated, forward the results to the output layer. In terms of text categorization the *tokens*, represented through a *term frequency matrix*, are the input units which are e.g. weighted with respect to their occurrence and if the processing units are activated, are propagated forward to the output layer where the output determines the respective categories. The training of the neural network evolves

---

<sup>5</sup>The Self Organizing Kohonen Map used in Chapters 2 and 3 belongs to this family of computational models.



similar as for the other machine learning algorithms. The system is fed with texts at the input layer and with respective categories at the output layer. If the network delivers misclassifications, the errors are fed back or backpropagated into the network in order to correct the weightings until the classification task is fulfilled sufficiently. The core of each artificial neural network are the activation function, the error or cost functions respectively and the backpropagation algorithm. In linear cases the activation function is simply the weighted sum of inputs. For non-linear tasks often sigmoidal activation functions are used. If the activation function, which depends on the inputs and initial weights, delivers an output, a classification, which is different to the desired one, the error value is calculated by the cost function. The backpropagation algorithm then allows to determine in what way the error depends on inputs, outputs and weights and in combination with the cost function to calculate how the weights can be changed in order to receive a lower classification error. This weight correction is conducted iteratively until the network recognizes patterns for respective classes correctly. Complex forms of Artificial Neural Networks use numerous hidden layers with corresponding activation functions and backpropagation algorithms. The design of the network strongly depends on the classification task and needs a lot of fine tuning (Sebastiani, 2002; Strecker, 1997). Noteworthy examples of applications of Artificial Neural Networks for text categorization come from e.g. Yang and Liu (1999) and Wiener et al. (1995). In the context of the here presented research project all four types of machine learning algorithms, and respective modifications, will be used and tested with regard to their performance.

#### 5.4.4 Annotation of Sentiment

Machine based sentiment analysis however doesn't go completely without human judgement. For the here envisaged task an annotated training data set is needed, which preprocessed with text mining techniques in order to make the textual information machine readable, can then be used to train machine learning algorithms, as outlined above, to automatically categorize texts in the real world and read out sentiments for specific data. Annotation in this context is the process of attributing sentiment (polarity) to documents of a training data set. The big advantage to traditional survey based sentiment indicators however is, that the task of data collection is nonrecurring.

In the context of the here envisaged construction of an economic sentiment indicator the Reuters RVC1 corpus (Lewis et al., 2004) was chosen as a training data set as it has the following advantages: It is already annotated with regard to topics and places, covers a sufficiently long time period (one year), it provides a sufficient number of documents to train with and it is freely available for research purposes. The documents in the corpus were preselected to sort out documents without any link to economic sentiment, articles about sports for example. This task was not very complicated as the news article in the Reuters RCV1 corpus are already labeled with topics.

The annotation of the training corpus with regard to polarity, all the other information is already contained in the RCV1 corpus, is then conducted via the crowd-sourcing website [www.insen.eu](http://www.insen.eu). This platform is an adaption of the *or-vis* software originally developed by Hirschfeld et al. (2010) at the University of Münster to conduct online



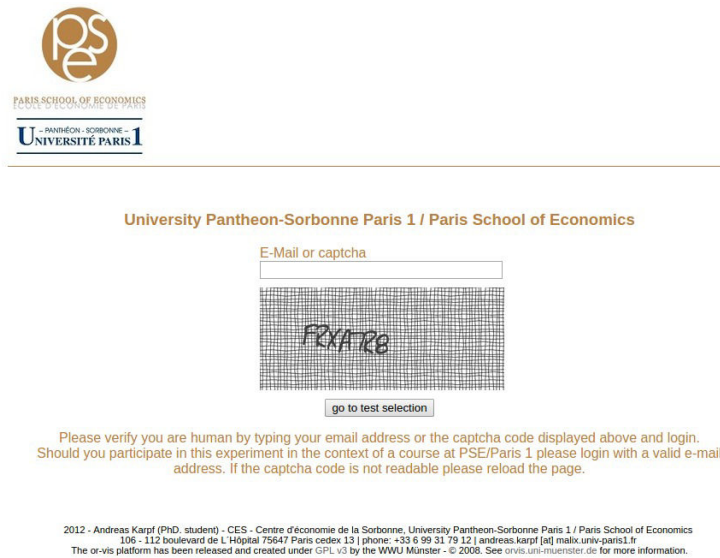


Figure 5.3: Startpage of the insen.eu crowdsourcing website

rating studies. The software was updated to run on modern servers and extended in terms of a new log in interface to allow for a greater anonymity of the participants, an extended capability to collect sociodemographic information and a more convenient data downloading function. Figure 5.3 displays the start page of the created crowd-sourcing website [www.insen.eu](http://www.insen.eu). After the log in and the choice of the study of interest (the software is able to host multiple crowd-sourcing projects simultaneously, see Figure 5.4), the participant is directed to an interface (see Figure 5.5) in which he/she is asked to provide basic sociodemographic information, as age, gender, education, occupation, family status, household size, the approximate household income, native language as well as information about their foreign language proficiency. The sociodemographic questions are important in order to ensure a better degree of representativeness. The latter questions about language skills are relevant as participants are supposed to evaluate texts in English language. After filling out these fields the participant is forwarded to the actual annotation task. In this section five random news articles of a subset of 16,324 news articles from the Reuters RVC1 corpus are presented to the participant. The subset of the RVC1 corpus is based on a preselection with regard to topics, as mentioned before news articles without economic relevance were discarded, and the presence of annotations supplied by Reuters: News articles were only included into the selection if they contained geographical information (country, city) and information about the industrial sector (the Reuters coding follows the same systematic as in the European Economic Sentiment Indicator [ESI]) concerned by the news. In the annotation task the participant is supposed to answer two question about each news article:



Figure 5.4: Selecting the respective study on [www.insen.eu](http://www.insen.eu)

1. How does the information in the news article describe the economic development in the past (e.g. in the last twelve months)?
2. Which implications does the information in the news-article have for the economic development in the intermediate future (e.g. in the medium term, the next twelve months)?

As outlined introductorily in section 5.2 qualitative choice options in the context of survey based sentiment analysis yield better results than quantitative answering possibilities. The participant is thus asked to select one out of three possible polarities with regard to the article evaluating the status quo (perceptions; Question 1) and the prospects (expectations; Question 2). Along the standards of survey based sentiment indicators three qualitative polarities will be at choice (EC, 2007): *positive*, *neutral* and *negative*. A news article as the example in Figure 5.6 could thus be annotated with a *positive* sentiment with regard to prospects and with a *neutral* sentiment for the status quo.

By now around 13,000 invitations to participate in the crowd-sourcing task were sent out, which has resulted at the time this text was written in around 3,000 annotated texts or 600 participants. Once a text was annotated it is removed from the pool from which the five texts for each participant are randomly selected. An article enters the pool again as soon all other texts were annotated.

A distributed approach in the described form also serves a secondary purpose mentioned in the literature. It resolves the problem to distinguish between subjectivity and objectivity of information, as described by Pang and Lee (2008): It evaluates the subjec-



### Information - Test procedure

Dear Ladies and Gentlemen,

Thank you very much for your participation. The following test will take approximately five to ten minutes. Five paragraphs will be presented to you. These texts are short news articles with economically relevant subjects. Please read these texts carefully. Each of the five texts will contain the following two multiple choice questions which you will be asked to answer:

- How does the information in the news article describe the economic development in the past (e.g. in the last twelve months)?
- Which implications does the information in the news-article have for the economic development in the intermediate future (e.g. in the medium term, the next twelve months)?

The response options are: positive, negative, neutral. Please imagine that you are reading these texts in a current newspaper, ignoring any reference to past events, dates or locations, and make your judgments accordingly.

Before the survey begins, we ask that you please complete the form below. The information is optional and absolutely anonymous.

Thank you very much for your support!

Age

Sex: ☐ male ☐ female

Occupation: ☐ full time employment ☐ part time employment ☐ self employment ☐ student ☐ retired ☐ unemployed

Education: ☐ less than High School ☐ High School ☐ some College ☐ College degree ☐ Graduate degree ☐ PhD

Family status: ☐ single ☐ relationship ☐ civil union/married ☐ divorced/widowed

Household size: ☐ 1 ☐ 2 ☐ 3 ☐ greater than 3

Household income: ☐ Less than 10.000\$ (€) ☐ 10.001\$ (€) - 25.000\$ (€) ☐ 25.001\$ (€) - 50.000\$ (€) ☐ More than 50.000\$ (€)

Native language ☐ English ☐ other

Which foreign languages do you speak and since how many years?

1.  since  years

2.  since  years

3.  since  years

[continue](#)

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206 - 112 boulevard de L'Hôpital 75647 Paris cedex 13 | phone: +33 6 99 31 79 12 | andreas.karpf[at]mex.univ-paris1.fr  
The online platform has been released and created under GPL v3 by the WWU Münster - © 2008. See [crisis.univ-muenster.de](#) for more information.

Figure 5.5: Sociodemographic data collected by the [www.insen.eu](http://www.insen.eu) crowdsourcing website

tive sentiments of participants towards objective information in economic problem fields, delivered by news articles. As a second axis of sentiment annotation a similar approach to that suggested by Koppel and Shtrimberg (2006), described in section 5.3, is envisioned: news articles in the training corpus should be annotated in terms of polarities with respect to the market impact they have caused. Along the method proposed by Koppel and Shtrimberg (2006) news articles for which a positive/negative market impact with regard to a certain threshold can be measured will be labeled as favorable or unfavorable respectively. News articles without relevant market impact will be labeled as neutral. The polarity label with respect to market impact will serve as a control variable next to the sentiment measures gained through human annotation with the help of the crowd-sourcing platform as described above.

After preprocessing the annotated documents along the text mining techniques outlined in section 5.4.2, an annotated and machine readable corpus, represented through a term frequency matrix (similar to the exemplary matrix displayed in Table 5.1), will be available. This corpus can be used to train machine learning algorithms, four types of such algorithms were described in section 5.4.3, which will enable us to automatically recognize similar patterns in currently published and parsed out articles from the in-

ternet and to automatically attribute labels for polarities (prospect [expectations] and status quo [perceptions]), topics and places in the same way as in the training data set. Which type of machine learning algorithm will be chosen depends on cross-validation runs conducted on the annotated training data sample in which it will be tested which approach tags the documents most efficiently or with the smallest error rate respectively. It also has to be tested if it makes sense to use certain *parts of speech* for certain categorization tasks instead of all available tokens. For the automatic categorization with respect to topics, this was already briefly discussed in section 5.4.2, it might prove more efficient e.g. to only use *nouns*. The articles which are parsed out from the web in the purpose of automatically categorizing them of course also have to be preprocessed by means of text mining techniques in order that machine learning algorithms can work with them. In the same step however, similar or even identical articles can be found and sorted out to avoid redundancies. Measured over a certain period, for example every week, this approach will deliver more up-to-date and more regular sentiment information in a sample size which could never be achieved by survey based economic sentiment indicators. How the resulting sentiment indicator is constructed will be discussed in the next section.

#### 5.4.5 Constructing a Sentiment Indicator

Parsing out text documents from internet resources, potential sources were discussed in section 5.4.1, and automatically categorizing them over a certain time delivers a set of sentiments with regard to predefined topics (through the information which comes with RVC1 corpus) evaluating prospects (expectations) and the status quo (perception). Assume for example, that during an observation period 100 articles were automatically tagged with regard to a topic by the machine learning algorithm, out of which a *positive* sentiment was attributed to 60, a *negative* to 30 and a *neutral* to 10 with regard to the topic “consumption” and the time dimension “prospect”. For such results an indicator value can be calculated as it is done by the standard survey based indicators. The method which will be used for this purpose is equivalent to that outlined in the manual for “*The Joint Harmonised EU Programme of Business and Consumer Surveys*”(EC, 2007) published by the European Commission. Assume that for a certain time period<sup>6</sup> a sample of  $N_j$  documents was automatically categorized with the topic  $j = \text{industry, services, consumption, construction, retail}$  and the respective time referenced polarities  $P(\text{positive})$ ,  $E(\text{neutral})$  and  $M(\text{negative})$ . At the moment it should be assumed that only the sentiment for one geographical entity e.g. the European Union should be measured, letting aside at the present specific weights of member state countries. If  $P_j$ ,  $E_j$  and  $M_j$  stand for the respective percentile fractions in  $N_j$  of topic-sentiments with regard to  $j$  then the balance  $B_j$  is calculated as  $B_j = P_j - M_j$ . The balance indicator  $B_j$ , given data was collected over a sufficiently long period of time, will be seasonally adjusted using the Dainties approach (Fischer, 1995), a method which is also used by the European Commission branch for Economic and Financial Affairs,

<sup>6</sup>As such a time period one week could be considered.



20%

**Wage talks stall in S.African petroleum sector.**

South Africa's petroleum industry said on Sunday talks with the chemical workers' union on wages and working hours had stalled."The union rejected a ten percent across the board wage offer and a reduction in average hours worked, taking the maximum in the sector to 43 hours a week," said a statement by Simon Drysdale, chief negotiator for the petroleum industry.He said the union wanted shorter hours, a 12 percent across the board increase and a minimum wage of 1,800 rand a month.The union had refused to give an undertaking beyond Sunday (September 1) that it would not strike during wage negotiations, Drysdale said.-- Cape Town newsroom 2721 252238

Location: CAPE TOWN, SAFR | Date: 1996-09-01 | ID: 26299 | Industry: Energy and Water Supply  
Copyright Reuters Ltd. - Reuters Corpus, Volume 1.2 | Lewis/Yang/Rose/Li, 2004. RCV1: A New Benchmark Collection for Text Categorization Research, in: Journal of Machine Learning Research 5, pp. 361-397. (Except for experimental purposes only)

1. How does the information in the news article describe the economic development in the past (e.g. in the last twelve months)?

positive neutral negative

2. Which implications does the information in the news-article have for the economic development in the intermediate future (e.g. in the medium term, the next twelve months)?

positive neutral negative

proceed

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The or-vis platform has been released and created under GPL v3 by the WWU Münster - © 2008. See orvis.uni-muenster.de for more information.

Figure 5.6: Annotating sentiments to RCV1 articles on www.insen.eu

resulting into a seasonally adjusted balance  $X_{j,t}$  for a certain topic  $j$  and period of time  $t$ . A so gained seasonally adjusted time series of  $X_{j,t}$  would correspond to the sectorial sentiment indicators published by the European Commission on a monthly basis. The aggregate indicator will be constructed along the guidelines published by the European Commission (EC, 2006, 2007) in three steps. At first the deviation from the longterm average relative to the long term standard deviation is calculated,

$$Y_{j,t} = \frac{X_{j,t} - \bar{X}_j}{S_j}$$

with

$$\bar{X}_j = \frac{1}{T} \sum_{t=1}^T X_{j,t} \quad \text{and} \quad S_j = \sqrt{\frac{1}{T-1} \sum_{t=1}^T (X_{j,t} - \bar{X}_j)^2}$$

At the beginning obviously no reference sample is available with which the long term average and standard deviation could be calculated. Since the web-based sentiment in-

indicator and the ESI use the same standardization methods it however seems appropriate to use the respective long term values from the ESI at the beginning. The ESI uses a reference time series from 1990:1 until now. As soon own sentiment data is collected it should be used to extend the reference time series. Since the ESI data is only available on a monthly basis it has to be converted to weekly data by the means of interpolation. In a second step using sectorial weights the weighted averages are calculated divided by the sum of the weights <sup>7</sup>,

$$Z_t = \frac{\sum_j w_j Y_{j,t}}{(\sum_j w_j)_t}$$

In the context of the construction of a web-based sentiment indicator for the European Union sectorial weights equivalent to those used for the construction of the ESI will be applied<sup>8</sup>. For other geographical regions or countries sectorial weights will be taken from similar sources like regional survey based indicators. In the third step the weighted average  $Z_t$  is scaled to have a long term mean of 100 and a standard deviation of 10. As outlined before, at the beginning as long as not enough data was collected by the web-based approach, the long term values from the ESI index will be taken for this purpose:

$$webSI_t = \left( \frac{Z_t - \bar{Z}}{S_Z} \right) \cdot 10 + 100$$

with

$$\bar{Z} = \frac{1}{T} \sum_{t=1}^T Z_t \quad \text{and} \quad S_Z = \sqrt{\frac{1}{T-1} \sum_{t=1}^T (Z_t - \bar{Z})^2}$$

As the ESI, the web-based Sentiment Indicator, short *webSi*, will fluctuate around 100, where values above/below hundred will imply a positive/negative sentiment trend (EC, 2007, p. 20). The same approach will be applied for the sentiments which were extracted by the completely computerized method suggested by Koppel and Shtrimberg (2006).

## 5.5 Testing Economic Hypotheses and the Predictive Power

The so gained sentiment data cannot only be used to establish an Economic Sentiment Indicator as outlined above but also delivers a huge amount of sentiment information which could be used to test economic hypotheses for example that about expectational rationality. Two types of tests concerning the rational expectation hypothesis are possible. The first type demands a conversion of the qualitative sentiment information into

<sup>7</sup>This is important for the unlikely case that the sentiment of one sector couldn't be parsed out; this is relevant for survey based indicators but doesn't seem to be an issue for a web-based sentiment indicator as proposed here.

<sup>8</sup>Industry 40%, Services 30%, Consumption 20%, Construction 5%, Retail trade 5% (EC, 2007, p. 19)

quantitative data either by the probabilistic approach (Carlson and Parkin, 1975; Batchelor, 1986) or the regression approach (Pesaran, 1984; Pesaran and Weale, 2006b). For extensions of the probabilistic approach the reader is referred to Chapters 2 and 3. The so gained quantified data can then be used to test the rational expectation hypothesis as e.g. proposed by Pesaran and Weale (2006b), Pesaran and Smith (1995) or Bonham and Cohen (2001). A second type of rational expectations test, e.g. that proposed by Gourieroux and Pradel (1986) and conducted by Gardes et al. (2000), is able to handle qualitative data directly. Since the envisioned web-based Sentiment Indicator originally bases on individual sentiments towards publicly available information (see Section 5.4.4), it is also interesting to test Granger causality in the context of expectation formation for derived sectorial sentiment information and respective macroeconomic data as for example done by Carroll (2003). Further it would be interesting to check to what extent derived sentiment information can be used to forecast economic evolution e.g. along the example of Vuchelen and Praet (1984), Vuchelen (2004) who inter alia investigate the predictive power of various consumer sentiment surveys for private consumption. Likewise it shall be tested, following Matsusaka and Sbordon (1995), if and to what extent consumer confidence measured by the web-based Sentiment Indicator can explain aggregate economic fluctuations. The rational expectation hypotheses shall also be examined in the context of the literature on *sticky prices*, which give rise to overshooting reactions (Dornbusch, 1976), and *sticky information* (Mankiw and Reis, 2002): How and with what pace does economic sentiment adjust to structural shocks, be it monetary or informational shocks etc., in the economy? Does this adjustment process depend on informational rigidities, hence is information unequally distributed among households or firms? A paper which tests the expectational adjustment process in the context of shocks with consumer survey data from the United States stems from Coibion and Gorodnichenko (2012) and could serve as a model for similar examinations for sentiment data gained by the here presented web-based methodology.

## 5.6 Software and Ressources

All the above described tasks can be conducted by open-source text mining and statistics software. Examples are *GATE* (Cunningham et al., 2002), *R* (with the *tm*-package by Feinerer et al. (2008)) or *Rapidminer* (formerly known as Yale) (Mierswa et al., 2006). Also various Python libraries provide text mining techniques and machine learning algorithms. The basic model can be developed on a desktop computer or laptop, the application however is very resource consuming in terms of processing power depending on which quantities of data are parsed out from the web and treated. In this respect a computer lab where the processing power of many computers can be combined within a cluster would be helpful. For *R* an extension is available which allows distributed text mining in a computer cluster (Theußl et al., 2011).



## 5.7 Conclusion

**Advantages** An along the above described methodology compiled and published web-based sentiment indicator will be able to deliver more frequent and up-to-date sentiment information than the traditional monthly survey based sentiment indicators. This is due to three major advantages the web-based sentiment indicator has compared to traditional survey based indicators:

1. The crowdsourced annotation tasks outlined in Section 5.4.4 is nonrecurring. This means, once sufficient data was collected via the crowdsourcing website [www.insen.eu](http://www.insen.eu) and a machine learning algorithm was trained on this data set, it can be applied to an arbitrary number of new news articles parsed from online resources. Survey based sentiment indicators in contrast rely on regularly (monthly) conducting hundreds to thousands of interviews which is extremely resource intensive.
2. Single values of sentiment indicators are only useful when interpreted in the context of historic data. This means as far as survey based indicators are concerned that the data had to be collected over a sufficient amount of time (multiple years) in order to deliver some utility, for example to professional forecasters in the financial industry. This is a drawback which doesn't apply to the web based sentiment indicator: From news or internet archives one can parse data since the beginning of the widespread dissemination of web technologies at the beginning of the 1990ies. The web based sentiment indicator can thus be also applied ex post.
3. The internet produces terabytes of new, relevant textual data every day. This permits to collect and analyze sentiment data more frequently and delivers more up-to-date sentiment information than traditional survey based approaches.

**Status quo** By the time this text was written around 13,000 e-mail invitations had been sent out to participate in the the crowd sourcing task on [www.insen.eu](http://www.insen.eu). Up to now this has resulted in 600 participants or 3,000 annotated articles out of overall 16,324. Currently different alternative ways, possibly via social media, are evaluated to increase the number of participants. Once the crowd sourcing task is concluded, thus when all articles are annotated, one can begin to render the textual data machine readable using text mining techniques, train a machine learning algorithm and start to analyze new textual information from the web.

**Dissemination** The model developed in the course of this project should be finally implemented in a web application where users can query up-to-date sectorial or aggregate sentiment trends with regard to various geographical regions in order to track economic trends as they are emerging.





## Chapter 6

# A network-based analysis of the EU-ETS<sup>1</sup>

### 6.1 The Background - The European Emission Trading System

#### 6.1.1 The United Nations Framework Convention on Climate Change & Kyoto Protocol

The Kyoto Protocol (United Nations, 1998) from 1998 extends the United Nations Framework Convention on Climate Change (UNFCCC) (United Nations, 1992) which was negotiated during the UN Conference on Environment and Development 1992 in Rio de Janeiro by defining targets for the reduction of green house gas (GHG) emissions<sup>2</sup> into the atmosphere.<sup>3</sup> Following the principle of “*common but differentiated responsibilities*” as outlined in Article 3 of the Kyoto protocol (United Nations, 1998) which accommodates the responsibility of industrialized countries for the contemporary level of green house gas emissions, these targets were determined to be binding for the group of developed signatory states. This group is referred to as the Annex 1 parties with targets. The protocol was signed and ratified by 191 parties of which one was the European Union. Noteworthy exceptions are the United States and Canada. The United States of America signed but never ratified the protocol and finally withdrew in 2001. Canada eventually followed its neighbor in 2011 and quit the treaty.

The Annex 1 parties comprise 37 industrialized countries of which 28 are members

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<sup>1</sup>This chapter is based on an article written in collaboration with Antoine Mandel (Université Panthéon-Sorbonne) and Stefano Battiston (University of Zurich) forthcoming in the Springer ECCS Proceedings 2014.

<sup>2</sup>Green house gas emissions as defined in the Kyoto protocol include Carbon dioxide ( $CO_2$ ), Methane ( $CH_4$ ), Nitrous oxide ( $N_2O$ ), Hydrofluorocarbons (HFCs), Perfluorocarbons ( $PFCs$ ) and Sulphur hexafluoride ( $SF_6$ )

<sup>3</sup>The European Council ratified the United Nations Framework Convention on Climate Change in 1993 with the Council Decision of 15 December 1993 concerning the conclusion of the United Nations Framework Convention on Climate Change (European Council, 1993b)



of the European Union (at the time of the underwriting of the protocol 15 countries belonged to the European Union). The legally binding commitment of the signatory countries concerns the four green house gases carbon dioxide ( $CO_2$ ), methane ( $CH_4$ ), nitrous oxide ( $N_2O$ ), sulphur hexafluoride ( $SF_6$ ) as well as the gas groups hydrofluorocarbons ( $HFC_s$ ) and perfluorocarbons ( $PFC_s$ ). The targets itself are quantified in  $CO_2$  equivalents<sup>4</sup> and as percentages of the emissions in a base year. For the majority of the Annex 1 parties this base year is 1990. Exceptions are Bulgaria (1988), Hungary (1985 - 1987), Poland (1988), Romania (1989) and Slovenia (1986). The European Union as a whole committed itself to collectively reduce  $CO_2$  emissions by 8% until 2012 and by 20% until 2020 in terms of respective base year emissions. Table 6.1 lists the quantified emission reduction commitments of the respective European signatory countries for the commitment periods 2008 to 2012 and 2013 to 2020 respectively.

### 6.1.2 Flexible Mechanisms

To keep the costs of limiting  $CO_2$  emissions as small as possible for the signatory countries the Kyoto Protocol allows for so called “*flexible mechanisms*” which serve as an alternative to traditional approaches as for example carbon taxes or compensating measures as afforestation and reforestation (United Nations, 1998, Art. 3.3). These mechanisms comprise *International Emission Trading* (IET), *Clean Development Mechanisms* (CDM) (United Nations, 1998, Art. 12) and *Joint Implementation* (JI) (United Nations, 1998, Art. 6). International Emission Trading plays the central role of flexible emission reduction instruments and is complimented by the two latter mechanisms.

### Trading

The aspect of emission trading was initially negotiated into the Kyoto Protocol by the United States who had previously acquired positive experiences with market based emission reduction schemes in the context of the sulfur dioxide ( $SO_2$ ) allowance trading within the countries “*Acid Rain Program*” established by the Clean Air Act Amendments in 1990 (Schreurs and Tiberghien, 2007, p. 20). It bears some irony that the European Union member states which are now operating the biggest emission market in the world, were at the beginning in fierce resistance against this concept, which bases on a “*cap-and-trade*” principle (Ellerman and Buchner, 2007, p. 66). This means, permitted emission units so called allowance units<sup>5</sup> are allocated to emitters of green house gases. These assigned allowance units (AAU) normally depend on historical yearly green house gas emission data and are capped with regard to committed emission reduction targets. Thereby allowance units become a scarce good which participants can exchange/trade in a market context. Periodically (yearly) the market participants have to surrender the amount of allowance units in their possession. These are subsequently compared with the realized emissions, which are permanently recorded at the respective installations,

<sup>4</sup>The carbon dioxide  $CO_2$ -equivalent measures the amount of  $CO_2$  which has as much global warming potential to the atmosphere as a given amount of other green house gas emissions.

<sup>5</sup>One emission allowance unit typically corresponds to one metric ton of  $CO_2$ -equivalent.



Party	Commitment Period		base year
	2008 - 2012	2013 - 2020	
Austria	92	80	1990
Belgium	92	80	1990
Bulgaria	92	80	1988
Croatia	95	80	1990
Cyprus	-	80	1990
Czech Republic	92	80	1990
Denmark	92	80	1990
Estonia	92	80	1990
Finland	92	80	1990
France	92	80	1990
Germany	92	80	1990
Greece	92	80	1990
Hungary	94	80	1985 - 1987
Iceland	110	80	1990
Ireland	92	80	1990
Italy	92	80	1990
Latvia	92	80	1990
Liechtenstein	92	84	1990
Lithuania	92	80	1990
Luxembourg	92	80	1990
Malta	-	80	1990
Monaco	92	78	1990
Netherlands	92	80	1990
Norway	101	84	1990
Poland	94	80	1988
Portugal	92	80	1990
Romania	92	80	1989
Slovakia	92	80	1990
Slovenia	92	80	1986
Spain	92	80	1990
Sweden	92	80	1990
Switzerland	92	84.2	1990
United Kingdom	92	80	1990
European Union	92	80	1990

Table 6.1: Quantified emission limitation or reduction commitment (percentage of base year or period) (United Nations, 1998, 2012)

to check if the emission reduction targets were met. Installations can be factories, power plants or even aircrafts. If the available allowance units fall short of the realized emissions, the market participants have to pay a fine. This fine depends on the amount of allowance units by which the respective market participant misses its emission reduction obligations.

The concept of *International Emission Trading* exploits differing marginal abatement costs (MAC), this is the marginal cost of reducing green house gas emission by one unit, by for example countries, firms, industries or even between different branches within a company (Ellerman and Decaux, 1998).

### Clean Development Mechanism & Joint Implementation

The system of emission trading is complimented by the *Joint Implementation* and the *Clean Development Mechanisms*. In contrast to emission trading these mechanisms are project based. Grounded on the assumption that actions which lead to the reduction of greenhouse gases eventually have positive effects in slowing down global warming no matter where on the planet they are conducted, Annex 1 countries can engage in projects abroad which reduce green house gas emissions in order to earn emission reduction units (ERU). These emission reduction units in turn can be traded on the emission market or used when surrendering ones allowances at the end of a trading period. The Kyoto protocol hereby differentiates between two different mechanisms: The *Joint Implementation* mechanism is supposed to foster cooperation between Annex 1 countries in order to meet their emission reduction obligations. This means an Annex 1 country can invest into projects which help another Annex 1 country with lower marginal abatement costs to reduce its green house gas emissions. The resulting emission reduction units can then be reused domestically. The majority of currently ongoing Joint Implementation projects are situated in transition economies with Annex 1 obligations like the Russian Federation and Ukraine (Centre, 2014). For an overview of the number of ongoing JI projects and in this context issued ERUs and the countries where these projects are situated please consult Table 6.2.

The *Clean Development Mechanism* follows a similar idea but is targeted at non-Annex 1 countries. Although non-Annex 1 countries i.e. mainly developing countries don't have a legal obligation to reduce their greenhouse gas emissions, the Kyoto Protocol seeks to set incentives to implement accordant projects. These projects are audited by the United Nation Clean Development Mechanism Executive board (EB) and awarded with Certified Emission Reduction Units (CER). The quantity of CERs depends on the estimated abatement of green house gas emissions. The earned CERs can be sold to Annex 1 countries, which can use those to fulfil their emission reduction commitments. Under the principle of "*common but differentiated responsibilities*" the CDM pursues two goals: 1) It is supposed to help Annex 1 countries to meet their emission reduction commitments with the lowest possible costs by allowing them to profit from comparatively lower abatement costs in developing countries. 2) It sets incentives for developing countries to implement projects to foster sustainable development (United Nations, 1998, Art. 12). An overview of the current CDM projects can be found in Table 6.3.



Host country	Number of projects	Issued ERUs
Ukraine	321	503125
Russia	182	265053
Bulgaria	38	6949
Czech Republic	59	607
Romania	21	8938
Poland	40	19991
Hungary	13	7175
Estonia	14	817
Latvia	1	0
Lithuania	20	8531
Slovakia	2	0
Belgium	2	400
Germany	13	13250
Finland	3	972
France	17	9183
Greece	2	0
Spain	3	0
Sweden	2	1340
New Zealand	8	3094
Total JI countries	761	849427

Table 6.2: Joint Implementation projects and issued ERUs in selected countries (Source: Centre (2014))

Host by region	Number of projects	Issued CERs
Latin America	1163	148263
Asia & Pacific	7124	972515
Europe & Central Asia	94	21517
Africa	250	63890
Middle East	107	26096
Total	8738	1232281

Table 6.3: Clean Development Mechanism project and issued CERs by world region (Source: Centre (2014))



## 6.2 The European Emission Trading Scheme

### 6.2.1 Legal & Political Foundations

The European Emission Trading Scheme was as much inspired by the Kyoto Protocol as it is a result of the European Unions characteristic as a supranational organization of sovereign member states and its unique legal construction. The legal foundations of coordinated European actions in environmental issues within the framework of the European Union can be traced back as far as to the Single European Act (SEA) from 1986 (European Union, 1986, Subsection VI, Art. 130r). This treaty not only legally implemented the idea of a common European market which involved the freedom of movement for goods, services and individuals but also made the topic of environmental protection an issue for the European Community as a whole (Ellerman, 2010). The treaty allowed for the first time (by decision of the European Council) to take action on environmental matters on the basis of majority decisions (European Union, 1986, Art. 130s). Previously to the UNFFCCC and the Kyoto Protocol, attempts to limit green house gas emissions in a coordinated manner however failed. Exemplary for the special European case is the proposition of the European Commission in 1992 to introduce an Europe-wide tax on  $CO_2$  emissions (Schreurs and Tiberghien, 2007). The proposal however failed for three reasons: First, there was strong opposition of member states who feared to give up sovereignty. Although it was argued that environmental taxes would represent an exception, opponents feared that this could be a precedent to dislocate taxation rights which were and still are regarded as a privilege of the member states to the European institutions. Second, emission intensive industries lobbied against the idea (Ellerman, 2010, pp. 16). Third, Germany had concerns that a carbon tax could promote the use of nuclear power (Neuhoff, 2011, p. 61). The proposal of a common European carbon tax was finally put aside in 1997. Minimum tax rates on energy carriers were adopted as a compromise (Ellerman, 2010, pp. 16).

In the negotiations of the Kyoto Protocol during the third Conference of Parties to the UNFFCCC in 1997 the European Union member states demanded a binding and undifferentiated target for the reduction of green house gas emissions for all developed countries corresponding to 15% with regard to emission levels from 1990 until 2010. The, as mentioned above, incipient animosity against emission trading was reasoned by the concern that participants equipped with additional emission allowances could benefit from windfall profits eventually foiling the whole system. The success of the European Union within the negotiations was however limited. Instead of an undifferentiated 15% reduction commitment the parties agreed upon differentiated targets which correspond to an average reduction of 5.2% for each country with regard to the respective base years. Table 6.1 displays the green house gas emission reduction commitments in percentages of the base year emissions as they can be found in Annex B to the Kyoto Protocol. Within the internal burden sharing agreement (BSA) the European Union member states however agreed on differentiated targets (see Table 6.4). The final approval to include emission trading into the treaty by the European states was due to two factors: First, it was expected that the United States of America would be equally committed to the



Party	BSA Emission Target
Austria	87
Belgium	92.5
Denmark	79
Finland	100
France	100
Germany	79
Greece	125
Italy	93.5
Ireland	113
Luxembourg	72
Netherlands	94
Portugal	127
Sweden	104
United Kingdom	87.5
EU-15	$\cong 92$

Table 6.4: Emission Reduction Targets of the EU-15 along the Burden Sharing Agreement from 1998 with regard to the respective base years (given as percentage of the base year emissions) (European Council, 1998)

goals of the UNFFCCC and the Kyoto Protocol. Second, proponents of the emission trading concept could point to positive experiences with the  $SO_2$ -trading scheme in the United States and a carbon trading experiment within British Petrol (Ellerman, 2010, pp. 17). The Protocol was finally signed in New York on 29 April 1998 and adopted by the European Commission on 25 April 2002 by the Council Decision 2002/358/EC (European Commission, 2002).

### 6.2.2 The adoption of Emission Trading

In the aftermath of the underwriting of the Kyoto Protocol the resistance with regard to the implementation of a European emission trading scheme began to crumble. The following points were crucial in this process:

1. During the subsequent COP meetings in Argentina and Morocco, Japan rejected all attempts to give the United Nations the legal instruments to enforce the emission reduction commitments in the Kyoto Protocol through sanctions. It became therefore clear that an effective implementation of the goals formulated in the protocol in Europe could only be reached by an internal solution (Ellerman, 2010, pp. 17).
2. A further milestone is represented by the so called “*burden sharing agreement*” (BSA). The Kyoto protocol initially envisaged an undifferentiated reduction of the greenhouse gas emissions of the European Union by 8% until 2012 with regard to the GHG emissions in the base year 1990 (see Table 6.1). During the 2106<sup>th</sup> European Council Meeting 1998 the Ministers of Environment agreed on differentiated targets taking into account the respective economic situation of each member state.



The agreement from 1998 allots emission surpluses as high as +27% in the case of Portugal and reductions up to -28% as in the case of Luxembourg (see Table 6.4) (European Council, 1998). These obligations were codified legally binding in the Council Decision of 25 April 2002 concerning the approval, on behalf of the European Community, of the Kyoto Protocol to the United Nations Framework Convention on Climate Change (European Commission, 2002).

3. In 1998 and 1999 the European Commission published the reports “*Climate change - Towards an EU post-Kyoto strategy*” (European Commission, 1998) and “*Preparing for implementation of the Kyoto Protocol*” (European Commission, 1999) respectively discussing the possibility to implement a European emission trading scheme until 2005.
4. The legal basis for permanently monitoring emissions which is crucial condition for a cap & trade system already existed in the form of Decision 93/389/EEC (European Council, 1993a) and Directive 96/61/EC (European Council, 1996).
5. Ellerman (2010) note that the withdrawal of the United States of America from Kyoto Protocol in 2001 was a crucial moment. A condition for the successful ratification of the Kyoto Protocol was the support of at least 55 parties representing 55% of worldwide emissions in the base year 1990. Achieving such a majority was however difficult after the withdrawal of the United States. By giving its approval to the countries membership in the World Trade Organization (WTO) the European Union was however successful in taking Russia on board. This assured the successful ratification of the treaty. Along Ellerman (2010) this proved that the European Union was able to take leadership in internationally relevant issue and might have motivated the European member states to take it one step further.
6. The “*Green Paper on greenhouse gas emissions trading within the European Union*” published by the European Commission in 2000 finally already represents a conceptual layout of the future emission trading system. The green paper advises to adopt all three flexible mechanism defined in the Kyoto Protocol and suggests to concentrate on  $CO_2$  which is responsible for 80 % of the green house gas emissions in the European Union (European Commission, 2000, p. 11).

### 6.2.3 The legal implementation of the ETS

The European Union emission trading scheme was finally legally implemented by directive 2003/87/EC (European Parliament, 2003). In this text directive 2003/87/EC refers to the version with the following amendments:

- Directive 2004/101/EC of the European Parliament and of the Council Text with EEA relevance of 27 October 2004
- Directive 2008/101/EC of the European Parliament and of the Council Text with EEA relevance of 19 November 2008



- Regulation (EC) No 219/2009 of the European Parliament and of the Council of 11 March 2009
- Directive 2009/29/EC of the European Parliament and of the Council Text with EEA relevance of 23 April 2009

This directive along European Union law had to be transformed into national legislation. In France this was for example done by ordinance number 2004-330 from April 15, 2004 amending articles 229-5 to 229-19 of the French Environmental Protection Act (*Code de l'environnement*). In Germany the European Union directive was transformed into national law by the Greenhouse Gas Emission Trading Act (*Treibhausgas-Emissionshandelsgesetz* short *TEHG*) from July 15, 2004.

#### 6.2.4 Functioning

Like its precursor in the United States and as defined by the Kyoto Protocol the European Union Emission Trading Scheme relies on a cap & trade principle. The system is implemented and executed on a national level. Annex 1 of directive 2003/87/EC defines the concerned industries:

- cogeneration
- combustion installations
- oil refineries
- coke ovens
- iron steel industry
- cement, glass, lime, brick, ceramic, pulp and paper production

With directive 2008/101/EC the aviation industry was also included into the emission trading scheme (European Commission, 2008a). Under consideration of the emission reduction targets a specific amount of European Union Allowance (EUA) is assigned to each of the currently approximately 11.000 installations. An installation is a unit where one of the above listed activities is conducted i.e. for example a factory where bricks are produced (European Parliament, 2003, Art. 3 e)). One EUA permits to emit one ton of carbon dioxide equivalent during a specified period (European Parliament, 2003, Art. 3 a)). EUAs are transferable within the community but also to parties from third countries. This means a company which is not able to meet its emission reduction requirements can buy additional units on the market. Reciprocally if less units are needed than assigned, thus when the company is very effective in its abatement measures, excess units can be sold.



### 6.2.5 Surrender and cancellation of allowances

The member states have to ensure that, by 30 April each year<sup>6</sup>, the operator of each installation surrenders a number of allowances, equal to the total verified emissions from that installation during the preceding calendar year. The surrendered allowances are subsequently cancelled (European Parliament, 2003, Art. 3). Each member state has the obligation to hold any installation operator or aircraft operator who doesn't surrender sufficient allowances liable to pay a penalty. The penalty for each excess unit of emission i.e. each excess ton of carbon dioxide equivalent is currently EUR 100. Additional to the fine, operators have to surrender an amount of allowances equal to those excess emissions when surrendering allowances the subsequent year. The names of operators who don't fulfil their obligations are published. Since the beginning of 2013 the fine is linked to the development of consumer prices (European Parliament, 2003, Art. 16).

### 6.2.6 Banking and Borrowing

Operators are allowed to bank and respectively borrow allowances within a trading period. This means an allowance unit of one year can be used in the subsequent year (banking) or preceding year (borrowing) (Ellerman and Joskow, 2008; Gulli, 2009). The latter is possible because the allowances are issued on February 28 (European Parliament, 2003, Art. 11, 2) each year while the allowances from the preceding year have to be surrendered by end of April. This means one could use allowances from the subsequent year when surrendering the allowances for the preceding year. It was however not permitted to carry allowances from Pilot Phase I (2005 - 2007) to Phase II (2008-2012), and from there to Phase III (2013 - 2020) (Ellerman and Joskow, 2008, p. 3).

### 6.2.7 The allocation of allowances

The allocation of allowances in Phase I (the pilot phase) and Phase II (the actual first commitment period as defined by the Kyoto Protocol) followed so called National Allocation Plans (NAP). This means member states were not only autonomous in deciding upon their allocation of emission allowances but also to choose their abatement trajectory. The respective NAPs had to be audited and authorized by the European Commission along the criteria formulated in Annex II of the original version of directive 2003/87/EC. Along these criteria the NAPs had to take into account the emission reduction obligations which were fixed in the burden sharing agreement from June 1998 (European Council, 1998) and transformed into European law by Council Decision 2002/358/EC (European Commission, 2002) considering also that the ETS only covers  $CO_2$ , which only represents a fraction (if also the biggest) of overall green house gas emissions. Along these criteria member states are amongst others further demanded to take into account average emissions for similar installations as well as the technical feasibility of abatement and not to discriminate between different companies or industries. Each member

<sup>6</sup>For an overview of the process of the European Emission Trading scheme over the trading year please refer to Table 6.5.



state had to publish a list with all national installation covered by the European Union emission trading scheme and the respective allowances allocated to these installations. Along Article 11 of the original version of directive 2003/87/EC in Pilot Phase I (2005 - 2007) the member states were asked to allocate at least 95% free of charge. This practice is referred to in the literature as “*grandfathering*”. The remaining emission allowances were allowed to be allocated by auctions. In Phase II (2008-2012) this minimum was set to 90% (see also (Ellerman and Buchner, 2007, p. 73)).

Starting with Phase 3 in 2013 the capping and allocation process was changed considerably. The implemented reforms have significantly decreased the degree of autonomy member states enjoyed in Phase I and II. With the trading period 2013 the capping of emission allowances was moved from the national to the European level. As prescribed by directive 2009/29/EC (European Commission, 2009, preamble pt. 13) which amended the original ETS directive 2003/87/EC for the remainder of Phase 3 until 2020 the amount of allocated allowances will be decreased by 1.74 % annually. This cap is measured with regard to the average number of allowances issued by the member states in Phase II (2008 - 2012). The centrally prescribed cap should on the one hand ensure a better predictability, facilitate the planning for operators of installations and of course ensure that the emission reduction target of -20% with regard to 1990 green house gas emission levels until 2020 is met (European Commission, 2009, preamble pt. 4).<sup>7</sup> Directive 2009/29/EC also allots a gradual change to auction as far as allocating emission allowances is concerned as it is “... *the simplest, and generally considered to be the most economically efficient system.*” (European Commission, 2009, preamble pt. 15) not least because it is expected to decrease the likeliness of windfall profits. This is also the reason why beginning with 2013 the entire amount of emission allowances dedicated for the power sector is allocated by auctions, “... *taking into account its ability to pass on the increased cost of CO<sub>2</sub>*”(European Commission, 2009, preamble pt. 19) to the costumer: One of the main points of critique during the previous two trading phases were the windfall profits the power sector was able to generate due to the free allocation of allowances (Ellerman and Joskow, 2008, p. 30). For other sectors 80% of the allowances were still allocated by grandfathering in 2013. This fraction should however be gradually decrease each year to eventually reach 30% by 2020 (European Commission, 2009, preamble pt. 21).

### 6.2.8 Registries

The ETS directive in its original form applicable in Phases I and II of the European Union emission trading scheme prescribes the establishment of registries for each member state. These registries function as some sort of accounting system recording the issuance, allocation and cancellation of allowances as well as transactions. This along the directive should guarantee maximal transparency and “*ensure the accurate accounting of the issue, holding, transfer and cancellation of allowances*”(European Parliament, 2003, Art. 19). With directive 2009/29/EC (European Commission, 2009) which amended directive

<sup>7</sup>see also (European Commission, 2008b)



<b>Issuance and allocation</b>	before February 28 each year for the subsequent trading period
	↓
<b>Verification of emissions</b>	reporting the verified emissions for the preceding trading period before March 31 each year
	↓
<b>Surrendering of allowances</b>	surrendering an amount of allowances equivalent to the verified emissions before April 30 each year
	↓
<b>Publication</b>	Publication in the CITL before May 15 each year

Table 6.5: Sequence of the European Emission Trading Scheme over a trading period (Trotignon and Delbosc, 2008, p. 5)

2003/87/EC this function is resumed by a central Community Independent Transaction Log (CITL).

### 6.2.9 The Linking Directive: Joint Implementation and Clean Development Mechanism

European Parliament and Council directive 2004/101/EC (European Parliament, 2004) in the literature often denominated as the “*Linking Directive*” (Ellerman and Joskow, 2008, p. 4) amends the ETS directive 2003/87/EC by integrating the two project based flexible mechanism from the Kyoto Protocol namely “*Joint Implementation*” and “*Clean Development Mechanism*”<sup>8</sup> into the European Union Trading Scheme. It thus allows participating operators to acquire Certified Emission Reductions (CERs) from Clean Development Mechanism projects in third countries or Emission Reduction Units (ERUs) from Joint Implementation Projects in other Annex 1 countries. These allowances can be used equivalently to EUAs when surrendering allowances end of April each year. There are however two limitations: First, each member state has the right to set an upper limit for the use of CERs and ERUs. These limits differ between member states and are in the range between 0% (Estonia) and 22% (Germany) (Vasa, 2010; Ellerman and Joskow, 2008). Second, CERs and ERUs from nuclear facilities are explicitly excluded (European Parliament, 2004, preamble pt. 8).

## 6.3 The data set

The transaction data set containing the exact time stamp of the transaction and its volume as well as information about the accounts active in the ETS and data with regard to the allowance allocation, the surrendering of the allowances as well as the verified emissions were scraped from the CITL. The raw data set contains approximately 520,000 transactions to which we added spot price information downloaded from Bloomberg as well as data about the ownership structure and the type of companies in the ETS from the “Ownership Links and Enhanced EUTL Dataset” (Jaraite et al., 2013). In our analysis

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<sup>8</sup>outlined in Section 6.1.2



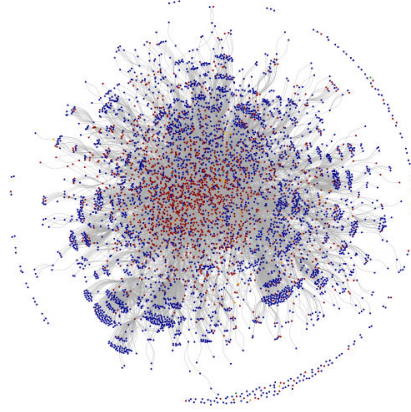


Figure 6.1: The CO2 trading network [CDM (green),finance (red),foundation (yellow), government (orange), industry (blue)]

we concentrate only on the market movements which are relevant for the price formation of the EUA certificates (transaction types 3-0, 3-21 and 10-0). Transactions connected to the administration of the ETS as for the allowance issuance, retirement, cancellation, surrender, allocation, and correction were discarded. The remaining 364,810 transactions are analyzed in what follows.

## 6.4 Methodology and research questions

A network based analysis of the European Emission market is performed. A network based on the transaction data set is therefore constructed. Thereby agents active in the emission market are regarded as vertices. These vertices are connected by directed edges in the form of transactions from the seller (the source vertex) to the buyer (the target vertex). The edges are weighted by the volume of EUAs transferred in the respective transaction. Figure 6.1 shows a plot of the resulting network graph. The aim is to investigate the connection between the network structure and the functioning of the market. In this context the following research questions are to be addressed:

1. Is the organization of the market reflected in the structure of the network?
2. Which factors are relevant for the matching process on the EU ETS?



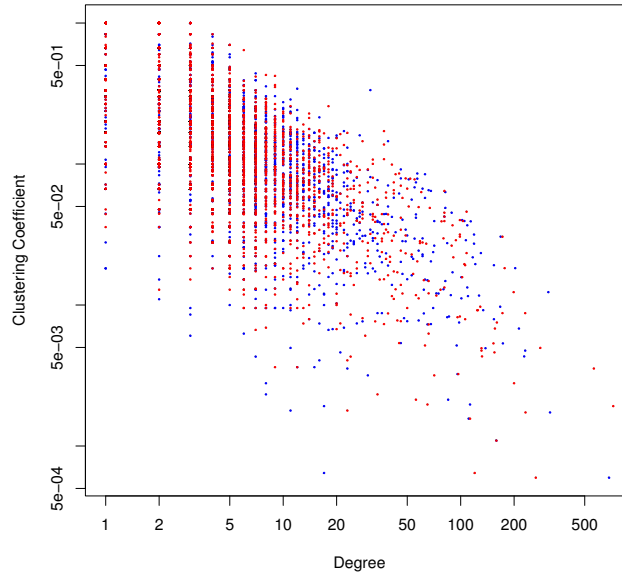


Figure 6.2: In-/Out-Degree vs. Cliquishness (in-degree: blue; out-degree: red)

3. Is the network structure supporting the idea of emission markets to exploit differences in marginal abatement costs?
4. Does the position of an agent within the network have an implication for its ability to create revenues out of a trade?

## 6.5 The Network structure of the European Emission markets

Along Li and Schürhoff (2014) some tests with regard to the market structure were conducted. Figure 6.2 plots the in- and out-degrees<sup>9</sup> vs. the cliquishness<sup>10</sup> of agents. The downward sloping cloud implies a hierarchy in the market with a strong core of highly connected nodes and clusters of nodes on the periphery. This phenomenon can also be observed in the plot of the emission market network in Figure 6.1.

The core periphery structure of the trading network is also observable when looking at the degree distribution directly (see Figure 6.3): The distributions of the in-, out- and total-degrees follow a power law i.e. there are agents whose in-, out- or total degrees

<sup>9</sup>The in- and out-degrees of each agent: this means the active and passive connectedness of agents.

<sup>10</sup>Be the  $k$ -core of graph a maximal subgraph in which each vertex has at least degree  $k$ . The cliquishness or coreness of a vertex is then  $k$  if it belongs to the  $k$ -core but not to the  $(k+1)$ -core (Seidman, 1983).

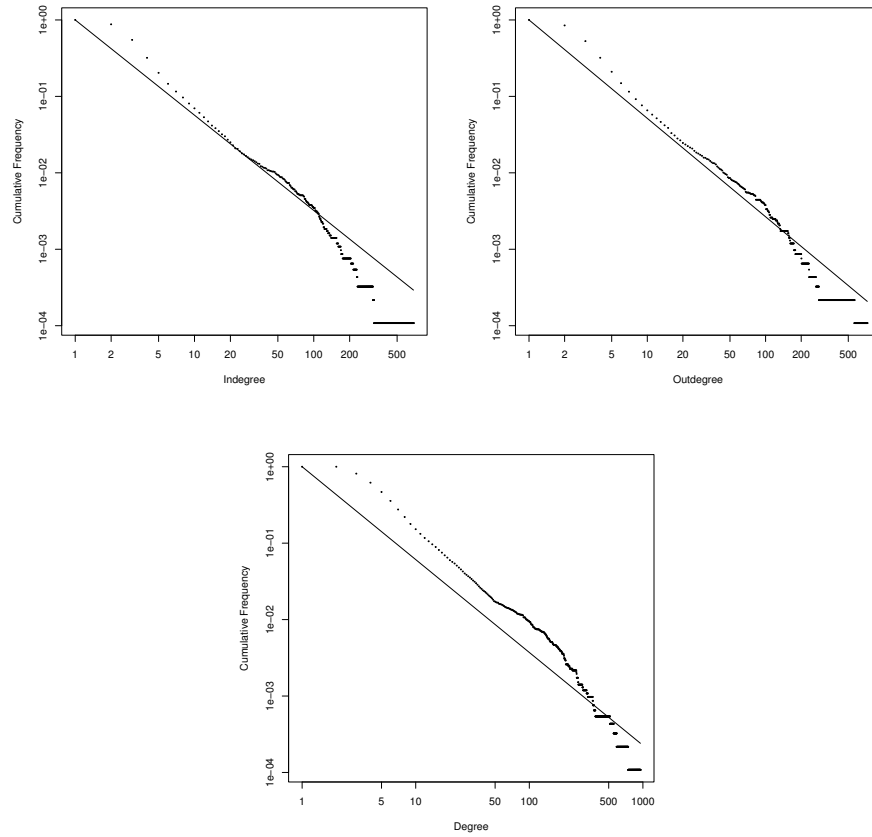


Figure 6.3: In-/Out-/Total-Degree distribution with fitted power law

strongly exceed the average. The exponents of the power-law distributions fitted to the in-, out- and total-degree-distribution are 2.25, 2.29 and 2.21 respectively. A conducted Kolmogorov-Smirnov test on the degree distributions resulted in p-values of 0.76, 0.97 and 0.96 respectively, indicating that the hypothesis that the original data could have been drawn from the fitted power-law distributions cannot be rejected in several cases. The observed network thus falls into the category of scale free networks. We further computed the density distribution of multiple network statistics (in-, out- degree as well as eigenvector centrality <sup>11</sup>) as well as for profits of companies in the European emission market combined with informations about their type. In this case the core-periphery structure is observable in the wave-like forms of the density plots displayed in Figure

<sup>11</sup>Eigenvector Centrality: the first eigenvector of the adjacency matrix giving the centralities for each vertex. It can be understood as a reciprocal process in which the centrality of a vertex depends proportionally on the centralities of other vertices to which it is connected. For a more detailed explanation the reader is referred to Section 4.4.4.

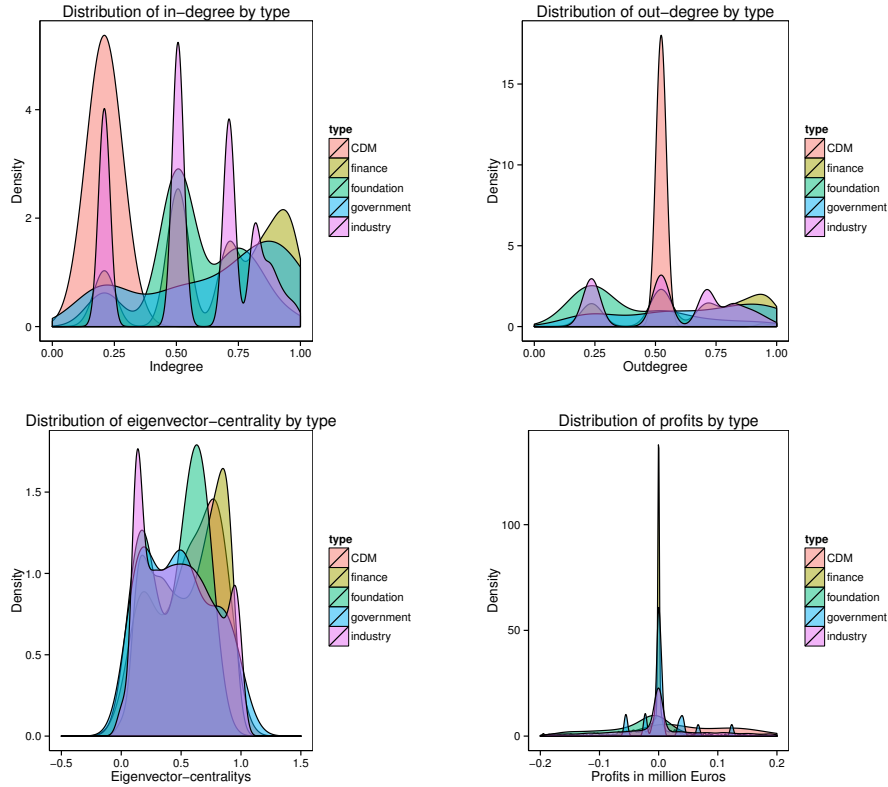


Figure 6.4: Densities plots for various trade network statistics and company types in the ETS

6.4. This structure is also reflected in the network plot in Figure 6.1 which has a highly connected center which is dominated by nodes from the finance sector (red) surrounded by concentric circles of nodes from the industries legally concerned by the ETS (OHAs). Going from the inside to the outside the nodes are lesser connected and thus exhibit a lower degree of centrality. Looking at the plot in the lower right of Figure 6.4 this, at least for the group of agents which can be attributed to the sector government, seems to have an influence on the profits these respective agents are able to derive from trading on the emission market.

## 6.6 Network position, trading volume and profits

To further investigate the connection between the position of an individual company within the network and its market participation (trade volume) on the one hand and its ability to derive profits from the market on the other hand we follow Boyd et al. (2010) in computing more sophisticated individual coreness values than the  $k$ -core (cliquishness) measure which was used above. Boyd et al. (2010) show that a singular value decom-

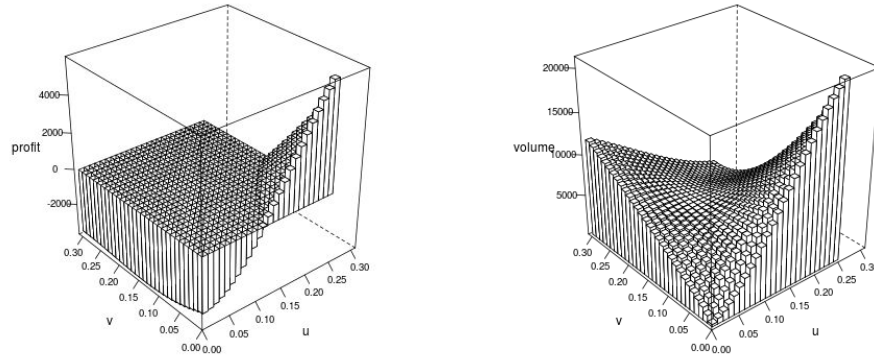


Figure 6.5: Elevation plots of out- ( $u$ ) and in- ( $v$ ) coreness values with respect to the generated profits and market participation (total volume traded) of individual agents

position (SVD) of the adjacency matrix combined with a prior imputation of missing values on the diagonal represents a fast and reliable method to compute the out- ( $u$ ) and in-coreness ( $v$ ) of individual agents within a large graph. The coreness of an agent is high, if an agent is well connected with other well connected agents. The SVD is methodologically and in terms of interpretation similar to the eigenvector centrality discussed above. The so computed coreness values as well as information about agents profits and volumes traded in the market were then used in combination with interpolation by means of local polynomial regression fitting to create the elevation plots displayed in Figure 6.5. Looking at the plot on the left-hand side in Figure 6.5 it appears as the ability to generate profits on the ETS positively depends on the out-coreness of an individual. The market participation on the other depends positively on both the in- and out-coreness of an agent. As far as the in-coreness is concerned this effect seems to be slightly weaker.

## 6.7 Network formation

The results from the last two sections can be interpreted as some kind of informational asymmetry in the market. OHAs which are legally forced to participate in the emission market and are seeking to buy and sell emission certificates resort to local networks (firms from the same parent company, country, industry etc.) or to huge financial players which form the center of the trading network. This undermines the central idea of the emission market to take advantage of differentials in abatement costs. This interpretation is further supported when we take a closer look at the network formation process.

A basic method to within this class of approaches to investigate the formation process

of a network is the Maslov-Sneppen (Maslov and Sneppen, 2002) algorithm: comparing the empirical network with a quantity of random networks with the identical degree sequence and distribution allows us to generate degree-degree correlation profiles which permit to identify connectivity patterns between nodes of different degrees. The so called null-model is generated by systematically rewiring the original network: Two pairs of connected nodes  $A-B$  and  $C-D$  are randomly selected from a network and rewired in the fashion  $A-D$  and  $C-B$ . If the thereby generated new connections already exist the procedure is aborted and two new pairs of connected nodes are randomly selected and the rewiring attempt is repeated. Doing this sufficiently often, a rule of thumb suggests a number as high as ten times the number of edges, one obtains a random model with the same degree sequence and distribution as the original graph. This procedure is repeated multiple times. Then the generated null-models are compared with the original network. More precisely, we compare the number of edges between two nodes with degrees  $K_1$  and  $K_2$  in the empirical network  $N(K_1, K_2)$  and the mean in the generated random networks  $\bar{N}_r(K_1, K_2)$ :  $R(K_1, K_2) = N(K_1, K_2) / \bar{N}_r(K_1, K_2)$ . If the deviance of the empirical network from the null-model is significant can be assessed by computing the Z-scores:  $Z(K_1, K_2) = (N(K_1, K_2) - \bar{N}_r(K_1, K_2)) / \text{sigma}(K_1, K_2)$ , where  $\text{sigma}(K_1, K_2)$  is the standard deviation of  $\bar{N}_r(K_1, K_2)$ . This method works for directed and undirected networks. The results of the Maslov-Sneppen approach for the emission trading network are presented in Figure 6.6. The interpretation of degree-degree correlation profiles is twofold:

1. When interpreting the emission trading network as an undirected graph one recognizes a compared to the null model significantly increased connectedness between highly connected nodes (the red area in the upper right corner of the LHS plot).
2. In both the undirected and the directed case (RHS) we note significantly increased degree of asymmetric connectedness i.e. between low- and high degree nodes (the orange to red area along the axes). This is in line with the results of a strong core-periphery structure presented earlier in the paper.

A bit more involved but based on a similar idea is the class of Exponential Random Graph models (ERGM). A random graph  $Y$  is made up by a set of  $n$  nodes and  $e$  edges  $\{Y_{ij} : i = 1, \dots, n; j = 1, \dots, n\}$  where, similar to a binary choice model,  $Y_{ij} = 1$  if the nodes  $(i, j)$  are connected and  $Y_{ij} = 0$  if this is not the case. One can thus model the given network by

$$P(Y = y|\theta) = \frac{\exp(\theta^T g(y))}{c(\theta)}$$

where  $\theta$  and  $g(y)$  are vectors of parameters and network statistics respectively and  $c(\theta) = \sum \exp\{\theta^t g(y)\}$  is a normalizing constant corresponding to all possible networks. Evaluating above expression (as the number of possible outcomes vastly exceeds the number of constraining parameters this is usually done by Gibbs sampling) allows us to make assertions if and how certain nodal attributes influence the network formation



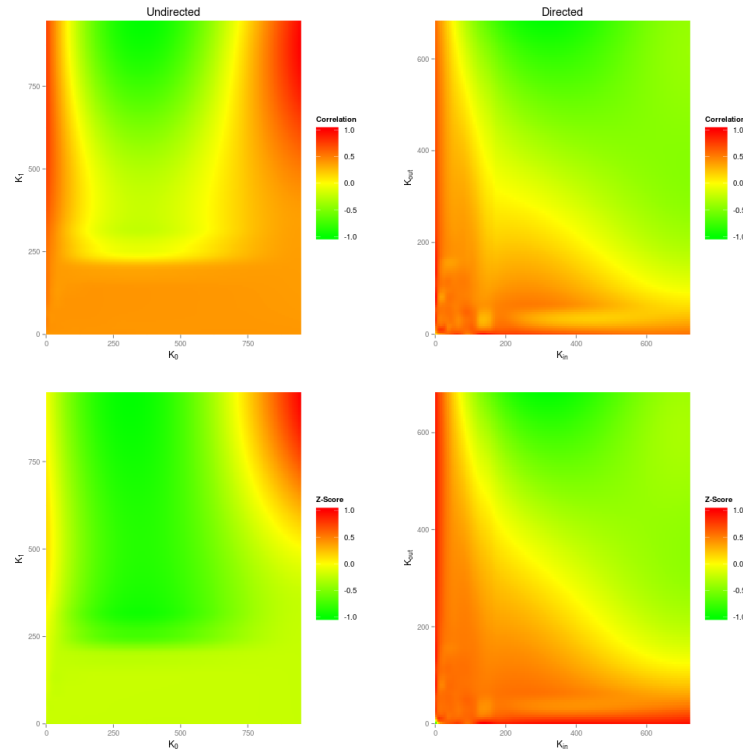


Figure 6.6: Degree-degree correlation profiles generated by the Maslov-Sneppen algorithm

process. These nodal attributes can be endogenous to the network, like the in- and out-degrees of a node, or exogenous as in the context of the trading network for example the country in which a specific company is registered.(Butts, 2014) We ran a basic ERGM model over the emission trading network. The results are presented in Table 6.6. The most important features of the results are as following: We observe positive log-odds for the closing of triangles (clusters), homophily for country and general ultimate owner (guo)respectively. We however remark negative log-odds for the formation of ties between agents of the same type (i.e. OHA vs PHA). We thus see what we already observed graphically earlier in the paper: OHAs who seek to sell or buy EUAs have to address themselves to local networks (homophily as far as origin [country] and ownership [guo] is concerned) or to financial institutions or brokers (heterophily with regard to type).

	<i>Dependent variable:</i>
	carbon network
edges	−4.785*** (0.172)
triangle	0.321*** (0.026)
asymmetric	−3.711*** (0.166)
nodematch.type	−0.099*** (0.019)
nodematch.country	0.392*** (0.031)
nodematch.guo	0.757*** (0.285)
Akaike Inf. Crit.	527,052.300
Bayesian Inf. Crit.	527,150.300
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01

Table 6.6: A simple ERGM model applied to the ETS network

## 6.8 Conclusion

The of above conducted network based analysis of the European carbon market yielded the following central results:

1. The European carbon market network is characterized by a significant core-periphery structure. This is on the one hand reflected in the apparent clustering behavior of agents in the market (see Figure 6.2) and on the other in the power-law nature of the degree distributions (see Figure 6.3). It can however also be verified by merely looking at the graph of the carbon market network (see Figure 6.1): We observe a highly connected core, which is mainly made up by players from the financial industry (PHAs). This core is surrounded by multiple layers of sparser connected nodes in the periphery which can be attributed to the industry (OHAs, i.e. agents who have a legal obligation to participate in the carbon market). This layered core-periphery structure can also seen in the wave-like form of the various density plots of individual-level centrality measures and profits displayed in Figure 6.4.
2. The core-periphery structure of the carbon market network is also reflected in the network formation process. Analyzing the degree-degree correlation profiles computed by application of the Maslov-Sneppen algorithm (see Figure 6.6) shows a strong asymmetry in the connection pattern between nodes, which is significantly



different to random null-models with the identical degree sequence and distribution: Weakly connected nodes have a tendency to connect to highly connected nodes and vice versa.

3. These results are supported when analyzing the network formation process in the European carbon market network by means of an exponential random graph model (ERGM): On the one hand we observe homophily as far a origin (country in which the company is registered) and ownership (global ultimate owner of the company) is concerned, on the other hand heterophily for company type (industry, finance etc.).
4. It is shown that the observed network topology has an impact on the market participation of agents (trading volume) as well as on the profits agents are able to derive from trading in the market (see Figures 6.4 and 6.5).

These results in our opinion reflect one major flaw in the organization of the European carbon market, which stands in stark contrast to the central idea of emission trading, namely to exploit differentials in marginal abatement costs in order to reduce the costs of emission reduction for participating OHAs to a minimum: The European carbon market is not organized in a central market place. The trading in the market bases, at least for the time the data was available, to a large extent on OTC transactions. OHAs which have the legal obligation to participate in the carbon market are forced to resort to local networks or financial intermediaries. The intransparent structure of the market imposes unnecessary additional costs, for example in the form of provisions, on OHAs, which often don't possess the resources to collect informations about the market themselves. The core-periphery structure of the market network should thus also be understood as a reflection of informational asymmetry in the market. This undermines the goal of the European Emission Trading System to economically reduce greenhouse gas emissions

The use of network analysis is new in its application to the European Emission market. Results in the literature however support our findings with regard to market inefficiencies in the EU ETS. Hintermann (2010) for example finds that, especially in the beginning of Phase I, EUA prices were not initially driven by abatement costs and that new information, with regard to fundamentals, like electricity prices or weather, were only incorporated with a substantial lag, thus indicating inefficiencies in the price formation process on the market. Palao and Pardo (2012) show the presence of price clustering in the European Carbon Futures Markets which they interpret as a sign of market inefficiency. This might be due to the weak price signal from the actual allowance market. Charles et al. (2013) investigate the European carbon markets, spot and future markets, during Phase II with regard to cost-of-carry hypothesis. The cost-of-carry model is rejected in all cases implying arbitrage possibilities and thus an inefficient functioning of the market.

The application of methods from social network analysis to investigate the functioning of markets in our opinion opens up a wide field of interesting questions for future research. It would be for example interesting to investigate which influence the dynamic



network structure has for the price formation or for the volatility of prices. Fitted exponential random graph modelling for example allows to simulate networks which have the same properties as the empirical network. Switching off certain factors in the simulation, as for example clustering, homophily, heterophily etc., would then permit a counterfactual study to what extent certain network properties have an influence on prices (and their volatility). Such a study is planned by the authors as follow up to what was presented above.



## Chapter 7

# Conclusion

The last five chapters investigated the role of social interactions for the expectation formation (Chapters 2 to 5) and in a market context (6). This conclusive chapter summarizes the results, outlines the methodological contributions and discusses topics for possible future research.

### 7.1 Summary, Results and Discussion

**Chapter 2** In Chapter 2 it was investigated which role herding behavior plays in the expectation formation of agents. Therefore a microlevel dataset from the French household survey ECAMME was transformed into a pseudo panel using self-organizing Kohonen maps (Kohonen, 1982). Thereby the individuals in the data set were grouped into cohorts which can be tracked over the whole available time frame. Basing on the contributions by Kaiser and Spitz (2002) a technique using a MCMC hierarchical ordered probit model was proposed to infer quantitative cohort-level estimates from the qualitative responses of survey participants with regard to their inflation expectations. A method proposed by Bernardt et al. (2006) to test herding behavior of professional forecasters was furthermore extended in a way that it can be directly applied to the cohort-level posterior distributions of the MCMC quantification procedure. In applying this test it was shown, that agents overall exhibit a strong anti-herding behavior in their expectation formation process and thus a bias away from the consensus. Anti-herding corresponds to an overweighting of individual information compared to public information (the consensus or the expectations of other people). Since the study was conducted on data with regard to inflation expectations this can be attributed to the different consumption behavior of different sociodemographic groups which is also reflected in different expectations as far as the future evolution of prices is concerned. This supports the hypothesis of heterogeneous expectations.

This result is backed by findings of other authors. Mankiw et al. (2004) for example finds using inter alia data from the Michigan consumer survey (this data was also used in Chapters 3 and 4) that there is, varying with the respective economic situation, great disagreement among agents concerning expectations with regard to the future



evolution of prices. A study by Pfajfar and Santoro (2009) finds evidence that consumers concentrate on the CPI relevant for their sociodemographic subgroup rather than on the general future inflation rate as it is surveyed by consumer surveys.

In this context it is interesting to note, that the test statistic is the closest to the margin between anti-herding and herding around the third and the fourth quarter of 2008, this means at the time when the global financial crisis was triggered by the bankruptcy of the Lehman Brothers investment bank. This finding was interpreted as a result of the intensive media coverage of this key moment in the recent economic history, which in the short term lead agents to attribute higher weight to public information.

Another possible interpretation of the results from Chapter 2 can be found in the work by Rülke and Tillmann (2011). The authors detect significant anti-herding behavior among non-voting members of the Federal Open Market Committee (FOMC), which they interpret as some sort of strategic behavior to influence monetary policy. This might also apply for interviewees in consumer surveys. Being interviewed by a public entity might be perceived by agents as one of the seldom chances to utter their opinion about economic (monetary) policy and thereby to influence it to a certain degree. Given the results in chapter 3 the interpretation with regard to heterogenous expectations however seems to be more likely.

**Chapter 3** In Chapter 3 the panel-structure of the Michigan Consumer Survey together with its questions about expectations and perceptions of the same variables were exploited to group respondents in the dataset into “rational” and “non-rational” individuals in order to explore the reasons for a “rationality bias” (a deviation from rationality). For variables without backward looking question (perceptions) a Hierarchical Ordered Probit (HOPIT) method proposed by Lahiri and Zhao (2015) was used in order to estimate individual-level threshold values and transform the realized values of the concerned variables (inflation and unemployment) from twelve months after the initial interview into individual-level perception estimates. Using a linear and non-linear Oaxaca-Blinder decomposition (Oaxaca, 1973; Blinder, 1973; Yun, 2004; Bauer and Sinning, 2008; Rao, 2009; Powers et al., 2011) the gap in expectations between “rational” and “non rational” individuals was analyzed.

It is shown that this expectational gap corresponds to an overly optimistic attitude of “non rational” individuals and can be explained to a large and significant extent by observable variables. These observable variables comprise sociodemographic information as well information from questions asked during the survey. One noteworthy observation was, that news consumption prior to the interview (a question in the Michigan Consumer Survey) turned out to be a significantly contributing factor in widening the rationality gap. These findings show that the so called “rationality bias” is thus not really a question of rationality but reflects the distinct experiences of individual agents.

It is noteworthy that this effect was weaker for variables, which to a high degree reflect the individual experience of agents, like inflation expectations or expectations with regard to personal finance. It was argued, that this might be due to the fact that these variables are determined by factors which can impossibly be captured by a



standardized consumer survey. A deviation from the rationality condition applied in this chapter might for example be due to unanticipated shocks to the financial situation of an individual. In this context one might think about maintenance work for housing or vehicles or medical bills which are connected with high costs for the individual and which were impossible to foresee at the date of the first interview.

These results are in line with the findings of Chapter 2 and hence also support the notion of heterogenous expectations. There is wide variety of both empirical and experimental research, which backs this conclusion. The studies by Pfajfar and Santoro (2009) and Mankiw et al. (2004) are two examples which were already cited above. The latter is especially noteworthy as Mankiw finds evidence for heterogenous expectations amongst others using data from the Michigan Consumer Survey which was also used in this chapter. Branch (2004) comes to a similar conclusion. He finds that agents in the Michigan Consumer Survey use a variety of costly predictor functions when forming their expectations of future price changes. Hommes (2011) uses a comparable method as Branch on experimental data, likewise showing evidence for heterogenous expectations. The same holds for the studies of Frankel and Froot (1987, 1990) and Taylor and Allen (1992), who both use data from professional forecasters.

**Chapter 4** Chapter 4 however shows that the expectation formation of agents is not completely free from social influence. Again in applying self-organizing Kohonen maps (Kohonen, 1982), this time to the Michigan Consumer Survey, cohorts of similar individuals were formed which can be traced over all the periods in which the dataset was available at the time this text was written. Then transfer entropy (Schreiber, 2000), a concept from information theory, was used, to estimate causality values (in both directions) between the discrete inflation expectation time series of each cohort. The discrete cohort-level time series were generated in using the cohort mean and subsequently applying a discretization approach by Meyer (2008), which yields frequencies similar to that in the whole data set. Thereby one is able to gain a notion of information flows in the expectation formation process and thus about social influence between different cohorts. It is shown that social influence depends on sociodemographic characteristics as age, education and income. Only looking at the strongest ties in terms of net-information transfer one is further able to construct a network of social influence. I find that social influence coincides with a high degree of connectivity and a central position within the network of social influences, which as many other networks observable in reality follows a power law and thus falls into the category of scale free networks.

**Chapter 5** In Chapter 5 a concept is proposed to collect economic sentiment information via modern web-mining techniques in combination with approaches from machine learning. The therefore created crowd-sourcing website [www.insen.eu](http://www.insen.eu) is presented, which serves the purpose of collecting human sentiment annotation for a training dataset basing on the Reuters RCV1 corpus which can, as soon as sufficient data is available, used to train appropriate machine learning algorithms. Once this nonrecurring annotation and training task is terminated the algorithm can be utilized to collect sentiment



information from freely available textual data on the web. It is argued that the proposed web based sentiment indicator is superior in multiple ways to traditional survey based methods to collect consumer or business sentiment information: 1) The task of data collection is nonrecurring. As soon as the training data set is annotated, for the time being around 600 individuals have participated in the crowdsourcing task and have annotated 3,000 out of 16,324 articles, and a machine learning algorithm was trained, the method can be applied to an arbitrary number of new articles. Survey based sentiment indicators on the other hand rely on regularly (monthly) conducting a high number of interviews, which is very resource intensive. 2) Sentiment indicators can only be usefully interpreted in the context of past data. For survey based indicators this implies that multiple years of data have to be collected until they can deliver any utility. The methodology outlined here in contrast permits to analyze data, for example from web or news archives, *ex post*. 3) Since the internet produces several terabytes of new relevant textual information every day the methodology described can deliver more frequent and up-to-date sentiment information than traditional survey based sentiment indicators.

**Chapter 6** In Chapter 6 the European Emission Trading System, established to economically and collectively reach the emission reduction targets as prescribed by the Kyoto Protocol, is analyzed from a network perspective. In the aim to investigate the connection between the network structure and the functioning of the market the notion of social interactions is thus brought to a market context. I find that the position of an agent within the network has an implication for its ability to create revenues out of a trade as well as for market participation, measured as volume traded, in general. Moreover we show that the carbon market network exhibits a strong core-periphery structure, characterized by a highly connected nodes, mainly made up by players from the financial industry, in the center, which is surrounded by multiple layers of weaker connected nodes, which can mainly be attributed to the industry, in the periphery. This topological characteristic of the network is also reflected in an asymmetry in the matching process. This is evident by the presence of clustering in the graph as well as by the power-law nature of the degree distribution. It can however also be shown by application of simulation based methods as the Maslov-Sneppen algorithm (Maslov and Sneppen, 2002) or Exponential Random Graph Models (ERGM) (Butts, 2014), which are able to deliver information about the network formation process: The Maslov-Sneppen approach shows that the network formation process is characterized by an asymmetry in the degree connection profiles. Weakly connected agents have a tendency to connect to highly connected agents and vice versa. Furthermore, applying an ERGM, we find heterophily as far as type (finance, industry etc.) is concerned on the one hand, homophily for origin and ownership on the other hand. The above described topology of the network as well as the network formation process can be interpreted as some sort informational asymmetry which is due to an inefficient functioning of the market. In the absence of a centralized market place, most of the transactions are over-the-counter, operators of installations which fall under the EU Emission Trading regulations have to resort to local networks or financial intermediaries if they want to buy or sell emission



certificates. It is argued that this imposes unnecessary additional costs for enterprises, for example in the form of provisions to brokerage firms, which undermines the central idea of the European Emission Trading System, namely to exploit marginal abatement costs and to keep the costs of emission reduction to a minimum.

The application of network analysis to the European Emission Trading System is novel. Our findings with regard to the network structure and the network formation process can thus unfortunately not be compared with existing studies. With regard to the notion of market inefficiencies other authors however come to similar conclusion using different approaches. A study by Hintermann (2010) for example finds, that especially at the beginning of Phase I prices on the European emission market were not driven by marginal abatement costs and that new information with regard to fundamentals, for example electricity prices or weather conditions, were only taken into account with a substantial lag. This hints to an inefficient price formation process on the market. Another study by Charles et al. (2013) tests the cost-of-carry hypothesis on several European carbon markets (spot and future markets). The hypothesis is rejected in all cases, thus indicating market inefficiency.

## 7.2 Methodological Contributions

In the following section an overview of the methodological contributions of this thesis should be given.

**Quantifying Inflation Expectations** Consumer surveys base to a large degree on qualitative rather than quantitative questions. This has on the one hand pragmatic reasons. Most surveys, like the ECAMME (used in Chapter 2) or the Michigan Consumer Survey (used in Chapters 3 and 4), rely on telephone interviews. Qualitative survey questions thereby have the advantage that they are easily comprehensible, as the interviewee is asked to choose one out of a limited set of, in the context of consumer surveys, normally ordered, answering options. On the other hand, as was already discussed for example in Chapter 2, as far as questions with regard to the future evolution of quantitative economic variables like the inflation rate are concerned, it turns out that individuals have a good sense for the trend, but often lack an accurate notion of the magnitude. The disadvantage however is, that, especially in the context of economic research, for some applications the qualitative survey data has to be quantified before it can be used. This was for example the case in Chapters 2 and 3. There is a multitude of different quantification methods, which can be roughly grouped into two categories: the regression approach (see for example (Pesaran and Weale, 2006a)) and the probabilistic (see for example Carlson and Parkin (1975); Theil (1952); Berk (1999) ) approach. Both were already extensively discussed in Chapter 2 and 3, thus only a short overview should be given here. The regression approach has a row of drawbacks: First, perceptions of price changes are assumed to be unbiased; second, it is assumed that inflation perceptions are formed along the same mechanisms as inflation expectations; third, this was the most important point for the research question in Chapter 2, it does not allow



to control for heterogeneity within participants. The probabilistic approach, also often denoted as Carlson-Parkin approach, on the other hand controls for some of these issues addressed above. The probabilistic approach for example doesn't make any assumptions with regard to the mechanism the inflation expectations are formed. The unbiasedness assumption can be circumvented by appropriate calibration. The raw results of the probabilistic approach are only identified up scale. For this reason I for example used in Chapter 3, following Lahiri and Zhao (2015), a time varying parameter model to calibrate the results. The probabilistic method however also has a number of drawbacks. In its standard implementation it as well doesn't allow to control for the heterogeneity of agents, it can't be estimated as soon as one answering option is completely missing in one period and the thresholds of the indifference limens are assumed to be symmetric and constant. Kaiser and Spitz (2002) show that the probabilistic method can also be estimated in an ordered probit framework which solves these issues. In Chapter 2 I show that this approach can be extended to a Hierarchical Bayes Markov Chain Monte Carlo Ordered Probit model. This has the same advantages as the method by Kaiser and Spitz (2002), however, by the inclusion of random intercepts allows to quantify qualitative inflation expectations on an individual- or, in the context of this study, cohort-level. This is the main difference to the maximum likelihood method along Lahiri and Zhao (2015) used in 3. Furthermore, it can handle relatively small amounts of cohort-level data and still gives good estimates as it borrows information from the whole population to gain individual-level or here cohort-level estimates. One can moreover run very complex estimations. The inclusion of explanatory variables is only limited by hardware restrictions.

**Testing herding behavior on huge data sets** The central method in Chapter 2 is the herding test proposed by Bernardt et al. (2006). It relies on the estimation of conditional probabilities with regard to the overshooting/undershooting of agents' inflation expectations compared to the consensus (see Section 2.3). In Section 2.8 it is shown how the test statistic by Bernardt et al. (2006) can be reformulated to a rank sum test in the style of the Wilcoxon test. This test shares the same statistical properties as the original test statistic by Bernardt et al. (2006), but can be computed, even for extremely large data sets, within seconds. In the context of Chapter 2 it was directly applied to the posterior distributions of cohort-level inflation estimates resulting from the Hierarchical Ordered Probit MCMC estimation. Moreover, in contrast to the original herding test by Bernardt et al. (2006) there is no concrete consensus value. The consensus is normally the mean or median of all extant forecasts for the same target value. In my modification of the test statistic the information of the entire posterior distributions of all other cohorts, when estimated for a single cohort, is exploited.

**Inferring networks of influence from survey data** Chapter 4 demonstrates a way to apply information theory, namely the concept of transfer entropy by Schreiber (2000), to consumers surveys in order to infer networks of influence. Barnett et al. (2009) show that transfer entropy is exactly equivalent to Granger causality for variables following



a Gaussian distribution. In its application to survey data transfer entropy however has the big advantage, that it can directly be applied to discrete variables, which spares the use of quantification methods as it was necessary in the chapters 2 and 3.

**Using text mining and machine learning to collect sentiment data** Chapter 5 shows how modern text mining and machine learning methods can be employed to collect sentiment data from textual information on the internet. The proposed web based sentiment indicator is more cost efficient, as the task of data gathering directly from individuals is nonrecurring, and can deliver more frequent and up-to-date sentiment information than traditional survey based sentiment indicators.

**A network based analysis of market** In Chapter 6 finally my coauthors Stefano Battiston, Antoine Mandel and me show how network science can be applied to analyze the structure and functioning of markets. This in our opinion has advantages to an outcome based analysis, multiple examples of such studies are cited in the conclusion of Chapter 6, as it allows to evaluate the micro structure as well as the matching processes at work on the market.

### 7.3 Topics for future Research

The work presented above opens up a range of interesting questions for future research. Some ideas should be discussed in what follows.

In chapters 2 and 3 I find that the expectation formation of agents is characterized by significant heterogeneity, a result supported by findings in other studies. In the context of Chapter 2 this heterogeneity of expectations with regard to inflation is reflected in a significant anti-herding behavior of agents, which was interpreted as due to the different consumption behavior of individuals. Especially in the context of the results around the third and the fourth quarter of 2008, when the global financial crisis started (see discussion above), it would be interesting to repeat this study for a variable which is more general, like the general business condition for example, and thus doesn't reflect so much on the individual financial situation of agents.

Furthermore it would be interesting to extend the methods of social network analysis employed in Chapter 6 for the analysis of the European carbon market, to a dynamic view of the market network. This would allow to investigate which influence the dynamic evolution of the network structure has for the price formation or for the volatility of prices. Together with the simulation from a fitted exponential random graph model this would permit to conduct a counterfactual analysis with regard to what factors in the network structure or in the network formation process have an influence on the market prices and their volatility respectively. Such a study is planned by the authors as follow up to what was presented above.

The transfer entropy measure used in Chapter 4 to infer a network of influence with regard to the formation of inflation expectations could also be applied in a non-economic context. The author for example already tested the same methodology to infer networks



of influence in the European Parliament using data from roll-call votes. This could for example serve to investigate the cooperation of members of the parliament aside party affiliations. A study of this kind is planned for the near future.



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