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# The Long-Term Evolution of International Stock Return Comovements

Tristan Jourde

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**THÈSE DE DOCTORAT**

**DE L'UNIVERSITÉ PSL**

Préparée à l'Université Paris-Dauphine

**The Long-Term Evolution  
of International Stock Return Comovements**

Soutenue par

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Le 23 novembre 2020

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*A mon frère, Rafaël*

“My ventures are not in one bottom trusted,  
Nor to one place; nor is my whole estate  
Upon the fortune of this present year;  
Therefore my merchandise makes me not sad.”

William Shakespeare, *The Merchant of Venice* (1598)

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# Introduction

Stock markets enable (i) households to invest their savings and to benefit from companies' expansion and (ii) firms to raise funds in order to develop their activities. Over the last decades, this role has considerably grown, along with the financialization and liberalization of the global economy. Between 1980 and 2018, the ratio of the world market capitalization to GDP tripled, from 31% to 93%. The number of listed companies more than doubled over the same period, from 17,273 to 43,342 (World Bank database, WDI).

Besides, the gradual liberalization of stock markets has led to increased cross-border equity flows, providing new sources of financing for companies and additional investment opportunities for investors. From 1995 to 2015, the purchases of domestic stocks by foreign shareholders grew fivefold in advanced markets, from 16% to 87% of GDP, and fourfold in emerging markets, from 4% to 16% (Lane and Milesi-Ferretti, 2018). At the same time, cross-border trade and financial links between companies have increased.

The liberalization of equity markets and the strengthening of international trade and financial links are likely to have led to rising interdependencies among stock markets (e.g., Quinn and Voth, 2008). These developments represent an essential matter for both investors and regulators, as rising stock market comovements may lessen the benefits of international portfolio diversification and undermine financial stability. This thesis thus explores the determinants and the consequences of the long-term evolution of international stock return comovements.

The remainder of this introduction is organized as follows: [Section A](#) describes the concept of comovements and presents the main theoretical mechanisms explaining stock market inter-

dependencies; Section B discusses the interests of studying stock market comovements for investors and regulators.

## A. Stock market interdependencies

We use the terms “interdependencies” and “comovements” indifferently. Comovements is a technical term that does not exist in standard dictionaries. According to Baur (2003), the concept of comovements shall be understood as con-movements, which means “moving with” or “sharing movement.” Barberis et al. (2005) also describe the notion of comovements as “a pattern of positive correlation.” Forbes and Rigobon (2002) use the term interdependencies to designate a context in which markets exhibit a high level of comovements. Without further specification, the terms interdependencies and comovements describe the relationship between two variables, in both normal and crisis times, and assume no causal link between them. These general concepts should be distinguished from more specific notions, such as “contagion” or “spillovers.” The literature uses the term contagion to describe an extreme adverse event in one market that affects others (Forbes, 2012). The notion of spillovers refers to the direction of shock transmission between markets, which implies the existence of dominating markets—net givers of shocks—and dominated markets—net receivers of shocks.

The theoretical literature proposes several hypotheses on the origins of stock market interdependencies. The first hypothesis states that stock market interdependencies reflect the existence of trade and financial links between countries. This idea stems from the work of Williams (1938) on firms’ intrinsic value. While the prevailing view in the 1930s was that financial markets behaved like casinos, Williams argued that the price of a stock should be equal to the present value of its future cash flows. Williams’ work found a wide resonance in the 1960s, with the emergence of the efficient market hypothesis. Under this hypothesis, stock prices are supposed to reflect rational investor expectations regarding firms’ intrinsic values.

The intrinsic values of firms are unlikely to be independent due to the existence of trade and financial links between countries and companies. A simultaneous adjustment in the intrinsic values of several firms should lead to common changes in stock prices. If this adjustment takes place at the international level, it can generate international stock return comovements. Based

on this principle, the theoretical literature describes several channels that might be at the root of the correlation among equity markets. The first channel refers to common shocks that might hit several economies at once (“monsoonal effect,” [Masson, 1998](#)). In addition, direct trade links might act as a channel for shock transmission between countries. A shock in one economy can reduce the demand for imports, affecting its main trading partners. Finally, shocks might spread across countries through direct financial linkages. A financial shock in one country can impact other countries through a reduction in loans, trade credits, or foreign direct investments, reinforcing stock market comovements.

Other studies assume that the interdependencies among equity markets can arise from the actions of irrational, uninformed, or constrained investors, even in the absence of trade and financial links between countries. Supporters of this second approach argue that the dynamics of stock prices cannot be comprehended without considering the human factor. Keynes describes investor behavior using an analogy based on a beauty contest. According to him, a financial analyst should not recommend the stock he or she believes is the best, but the stock he or she thinks other analysts will recommend. Therefore, variations in stock prices could depend more on speculation than on firms’ intrinsic value. In the 1980s, and especially after the 1987 stock market crash, researchers began to consider that stock prices are not always the best estimate of firms’ intrinsic value. If stock prices can significantly deviate from their fundamental values, stock market comovements can arise from investor behavior. Thus, previous papers have proposed new arguments based on investor behavior to explain these seemingly excessive stock market comovements.

First, shocks can spread across markets due to investor risk and liquidity constraints. A negative shock in a domestic equity market can force (i) risk-constrained investors to reduce their overall risk by selling their positions in other countries, (ii) leveraged investors to cut their exposures to pay for margin calls, and (iii) investment funds to liquidate some assets to cover redemptions (e.g., [Kodres and Pritsker, 2002](#)). Through these channels, an adverse idiosyncratic shock can be transmitted to other markets, leading to a synchronized decline in stock prices. Non-fundamental interdependencies might also stem from the existence of information asymmetry and coordination problems among investors (e.g., [Brennann and Cao, 1997](#)). With limited information on economic fundamentals, some investors may overestimate the expected

economic impact of an idiosyncratic shock in one country on neighboring economies. As a result, stock market comovements may depend more on investor’s limited knowledge than on the true fundamental linkages between countries. Finally, some scholars discuss the existence of multiple equilibria that may lead to sudden and simultaneous changes in investor expectations and confidence. This phenomenon, which is related to herding behavior, can also affect the degree of stock market comovements.

Over the past four decades, both international trade and financial links and cross-border equity holdings have intensified. These developments might help to explain the rise in equity market interdependencies over the past decades. We empirically test these hypotheses in [Chapter 2](#).

## B. Interests and applications

### *B.1. International diversification benefits*

The concept of comovements is intrinsically linked to the notion of diversification. The benefits of portfolio diversification are long-established. For example, Lowenfeld (1909) notes that: “It is significant to see how entirely all the rest of the geographically distributed stocks differ in their price movements from the British stocks. This individuality of movement on the part of each security, included in a well-distributed investment list, ensures the first great essential of successful investment, namely, capital stability” (as cited in [Goetzmann et al., 2005](#)).

The work of [Markowitz \(1952\)](#) marks a turning point in the world of asset management by proposing a formal framework to understand the link between correlation and diversification. [Markowitz \(1952\)](#)’s breakthrough is to demonstrate that investing in stock markets that exhibit low comovements with the rest of the world improves the return-to-risk profile of portfolios. More specifically, he shows that the variance of a diversified portfolio is lower than the average variance of its components. The reduction of risk depends on the comovements among the assets of the portfolio. [Chapter 1](#) describes the mathematical formulas associated with this concept.

However, Markowitz’s approach has limitations. First, the results of his model are sensitive to the input parameters. This shortcoming is exacerbated by the fact that it is difficult to es-

estimate expected returns with precision. More importantly, Markowitz’s framework is a static approach. The model assumes that the comovements among equity markets are constant, although many scholars argue that stock market comovements are not stable over time (e.g., Goetzmann et al., 2005, among others).

Changes in stock market interdependencies impact the benefits of portfolio diversification and can lead to significant losses for investors. Hence, the benefits of diversification tend to change over time, and optimally diversified portfolios may not be the same at different periods. Moreover, if the interdependencies among equity markets have increased over the past four decades, investors need to consider the possibility that the benefits of international portfolio diversification might not exceed its costs anymore. Therefore, in [Chapter 1](#), we study the evolution of the benefits of global diversification based on the simplified framework introduced by [Christoffersen et al. \(2014\)](#). This approach circumvents the main limitations of Markowitz’s methodology by focusing on the evolution of stock market comovements.

While many studies show that the comovements among equity markets have increased over time, others find less conclusive evidence (e.g., [Bekaert et al., 2009](#)). These contradictory results can be due to: (i) different methods of estimating comovements and testing for trends, (ii) diverse samples and periods of analysis, and (iii) distinct granularities of base assets—or data granularity. Our first contribution to the literature is to examine the impact of data granularity (i.e., country indices, local industry portfolios, or individual securities) on the long-term evolution of stock market comovements. We also show that the granularity of base assets affects the interpretation of the measures of international diversification. Consequently, [Chapter 1](#) proposes two alternative correlation-based measures that help reconcile some of the contradictory findings in the literature and shed new light on the evolution of the benefits of international diversification.

## *B.2. Financial stability*

Equity markets can impact financial stability and economic activity through several channels. First, stock markets influence the propensity to consume and save, particularly in countries where households invest a large share of their wealth in equity. Second, equity markets have an impact on the propensity to invest, since firms can raise more capital when stock prices are

high. Finally, stock markets can affect financial stability through their influence on the earnings of financial institutions. As the most interdependent stock markets are more exposed to external shocks, they are likely to pose a higher risk to financial stability (Berger and Pukthuanthong, 2012). Moreover, the rapid diffusion of the recent financial crises suggests that market interdependencies can accelerate and amplify the spread of shocks across countries (e.g., Forbes, 2012). Hence, growing comovements among equity markets might threaten the stability of the financial system, which is a crucial concern for regulators. In this respect, understanding the mechanisms behind stock market interdependencies is essential for designing proper policy measures.

The appropriate regulatory measures would differ whether stock market comovements arise from (i) trade links, (ii) financial linkages, or (iii) the irrational action of international shareholders. Moreover, the benefits and drawbacks of mitigating stock market comovements depend on the determinants of increasing interdependencies. If the rise in stock market comovements results from increased trade links, any attempt to reduce the degree of equity market interdependencies by implementing additional trade barriers could have higher economic costs than benefits. If growing interdependencies between stock markets are associated with increased financial links, such as bank loans, specific measures targeting bank leverage and imposing larger capital requirements might help mitigate stock market comovements without limiting the benefits of financial liberalization (Forbes, 2012). Finally, if the increase in equity market comovements arises from non-fundamental investor-based linkages, some policies targeting short-term equity flows in both source and receiving countries might prove useful (Ostry and Ghosh, 2013).

Mitigating stock market comovements arising from non-fundamental linkages is a more pressing issue than reducing fundamental interdependencies. Even in the absence of stock market comovements, a shock in one economy would ultimately impact the most interconnected countries through fundamental ties. In other words, fundamental comovements are likely to accelerate but not exacerbate the spread of shocks across countries. By contrast, non-fundamental interdependencies can transmit shocks between countries, even in the absence of fundamental links. Such interdependencies could both speed up and aggravate the propagation of shocks across countries.

Therefore, Chapter 2 aims to identify the mechanisms underlying the long-term evolution of international stock return comovements. This analysis can (i) provide regulators with useful information to preserve financial stability, and (ii) help investors forecast the evolution of stock market interdependencies. Indeed, with the rise of derivative markets, financial professionals can now take directional bets on the variations of stock market comovements. Our results enrich the findings of the previous literature, especially regarding the long-term impact of foreign shareholders on equity market comovements. We also contribute to the debate on the pros and cons of equity market liberalization.

Chapter 3 focuses on the interconnectedness of the insurance sector. The International Association of Insurance Supervisors (IAIS) defines insurers' interconnectedness as the "interlinkages of an insurer or the insurance sector as a whole with other parts of the financial system and real economy" (IAIS, 2018). The regulators consider that the complex chains of intermediation and interrelationships of insurance companies might have contributed to the spread of the subprime crisis throughout the world. As a result, the most interconnected institutions are now subject to additional capital requirements.

The ability to accurately estimate the level and risk associated with insurers' interdependencies is crucial for macroprudential authorities. Regulatory authorities have undertaken extensive work to collect data on balance sheet exposures to better monitor insurers' interconnectedness. However, detailed balance sheet data are only available in the short run and at low frequency. Assuming that stock market interdependencies reflect the actual links between companies—which is shown in Chapter 2 for advanced economies—measuring the interdependencies among the returns of insurers' securities can provide valuable information on insurers' interconnectedness. Studying the comovements between stock prices can thus serve as a substitute for the examination of the actual links between insurance companies.

In Chapter 3, we develop an interconnectedness measure based on stock market comovements that can be computed at a high frequency and over long periods. Such a measure is useful to identify the most interconnected insurers. Unlike previous studies, we focus on the long-term evolution and the specificities of insurers' interconnectedness with the rest of the financial sector and the real economy. This analysis can also provide indications on the evolution of the

probability and the potential economic repercussions of a crisis in the insurance sector. Finally, we discuss how our findings can help assess the need for the new holistic macroprudential framework implemented in 2020.

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## Chapter 1

# The Bright Side of the Decline in the Benefits of International Portfolio Diversification

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## 1.1. Introduction

Measuring international diversification benefits (IDB) is a crucial issue in the finance literature. Markowitz (1952) demonstrates that investing primarily in the least correlated securities improves the risk-return profile of portfolios. Based on this framework, the seminal paper of Grubel (1968) notes that stockholders can enhance the risk-return ratio of domestic portfolios by investing in foreign securities. In recent decades, the potential benefits of international diversification have become even more compelling, as financial integration broadened the pool of investment opportunities and reduced the costs of investing abroad (Goetzmann et al., 2005). However, Longin and Solnik (1995), among others, highlight that this process might have gone hand in hand with increased comovements among equity markets, leading to a decline in the IDB of equity portfolios.

Studying the dynamics of stock market correlation is thus critical to determine the evolution of IDB. Existing studies investigate this issue with contradictory results. Many scholars confirm that stock market correlation has increased over time (e.g., Pukthuanthong and Roll, 2009; Christoffersen et al., 2014; Eiling and Gerard, 2015; Billio et al., 2017; Jordà et al., 2019). On the contrary, other papers find no or limited evidence of a rise in equity market comovements (e.g., King et al., 1994; Berben and Jansen 2005; Kearney and Potì, 2006; Bekaert et al., 2009; Evans et al., 2017). These controversial conclusions could be due to (i) different methods of estimating correlation and testing for trends, (ii) various samples and periods of analysis, and (iii) distinct granularities of base assets (e.g., country indices, local industry portfolios, or individual securities).

This chapter explores the impact of data granularity on the long-term evolution of stock market correlation and the interpretation of the correlation-based IDB measure described by Christoffersen et al. (2014). We find that data granularity is a central consideration in studying the evolution of IDB. The standard in the finance literature is to analyze IDB based on the correlation between country indices. By contrast, using more disaggregated data leads to contradictory findings. We thus develop alternative indicators that yield consistent results regardless of data granularity and help reconcile previous findings. Another advantage of these alternative measures is to provide a decomposition of IDB's main drivers. Specifically, we highlight

that the decline in IDB is not as severe as it might seem, as it partly stems from the rise in the benefits of domestic diversification.

Our first contribution to the literature is to compare the evolution of stock market correlation using different types of base assets. This chapter complements previous papers by investigating both international and domestic relationships among local industries and individual securities. We show that using different types of data granularity leads to contradictory findings that we attempt to explain and reconcile. Moreover, our analysis uses up-to-date data, as we believe that the conclusions of the previous studies may be affected by the transitory impact of the global financial crisis (2007–2009) and the European debt crisis (2010–2012) on stock market correlation.

Second, this chapter discusses the impact of data granularity on the interpretation of the correlation-based IDB measure. We show that estimating correlation among country indices leads to an IDB measure that captures the relative gains of holding an international portfolio instead of the average domestic one (*relative IDB*). By contrast, estimating correlation among more disaggregated firm-level or local industry indices results in an IDB measure that compares the benefits of holding an international portfolio over the average stock or local industry portfolio (*absolute IDB*). Relative and absolute IDB measures can lead to different conclusions, as the relative IDB are also affected by the benefits of diversification within the domestic portfolio. We refer to these indicators as the *standard IDB* measures.

Third, we propose a relative IDB measure that makes the impact of data granularity on IDB negligible in most cases (*ratio-based IDB* measure). Specifically, we scale the absolute IDB measure by the domestic diversification benefits (i.e., the gain of holding a country portfolio instead of the average asset). The advantages of this adjusted indicator, compared to the standard one, are threefold: (i) it can consistently measure the relative IDB irrespective of the type of data granularity, (ii) it enables us to study IDB for different kinds of domestic investors, and (iii) it provides insights into the underlying forces driving the evolution of the relative IDB.

Fourth, this chapter points out that the variations in the global systematic risk (i.e., international factors) impact the standard and ratio-based IDB indicators. We argue that a reliable IDB measure should capture the ability to reduce diversifiable risk but should not be affected

by the level of non-diversifiable risk. Indeed, non-diversifiable risks have an identical impact on the (average) domestic and international portfolios, so they do not influence local investors' incentive to invest abroad. We thus propose an additional measure of the relative IDB based on the spread between the absolute benefits of international and domestic diversification (*spread-based* IDB measure). This indicator is more robust to changes in the global systematic risk than the standard and ratio-based IDB measures.

Beyond the methodological contributions, our empirical analysis enriches the existing literature in several ways. Based on a sample of 15 European stock markets over 45 years (1973–2018), we highlight that the choice of base assets (e.g., country indices, local industry portfolios, or individual securities) impacts the evolution of international stock market correlation. We find that the comovements between country indices have increased over time, while those among local industry indices or individual firms have remained more stable in the long run. Some papers argue that the increase in companies' international activities should lead to a permanent rise in the comovements among individual stocks around the world (e.g., Longin and Solnik, 1995). We do not confirm this hypothesis. Instead, we find some evidence that companies have become less correlated with the stock prices of other local firms. Therefore, IDB have declined over time in relative terms but have remained roughly stable in absolute terms.

Our findings are related to studies examining the impact of international activities on stock market correlation and factor loadings. Brooks and Del Negro (2006) find cross-sectional evidence that firms' international activities positively influence global factor loadings and negatively impact local factor loadings. Cai and Warnock (2012) and Berrill et al. (2019) also note that US multinational firms are (i) more exposed to foreign shocks than locally oriented firms and (ii) less correlated with the US domestic index, respectively. We complement these results by examining the dynamics of local and international stock market correlation over the past four decades.

Our conclusions are also linked to the literature studying the evolution of stock exposures to country, industry, and international shocks. While previous papers focus primarily on whether investors should diversify across countries or global sectors (e.g., Eiling et al., 2012), we examine whether domestic investors should invest abroad or stay at home. Some scholars also state

that the rise in comovements among country indices can stem from (i) an increase in global factor loadings, (ii) an increase in global factor volatility, or (iii) a decrease in idiosyncratic risk (e.g., Bekaert et al., 2009; Pukthuanthong and Roll, 2009; Eiling and Gerard, 2015). This chapter complements their approach by suggesting to decompose the rise in the correlation among country indices into (i) an increase in *international* comovements across firms or (ii) a decrease in *domestic* comovements across companies. The advantage of our framework lies in its direct implications regarding the benefits of portfolio diversification. Furthermore, asset-pricing models can be affected by missing or misspecified factors (e.g., Gagliardini et al., 2019), and previous studies generally do not attempt to infer the level of domestic and international intra-portfolio correlation from their results.

Finally, based on the standard and ratio-based IDB indicators, we confirm previous results showing that the relative IDB decreased from 1974 to the late 2000s but rebounded in the 2010s (e.g., Evans et al., 2017). On the other hand, the spread-based IDB indicator highlights that the relative benefits of international diversification mainly declined from 1974 to the end of the 1990s and did not rise again. This result suggests that most of the variations in the standard and ratio-based IDB measures from 2001 to 2018 resulted from changes in the global systematic risk. The spread-based IDB indicator, which is more robust to shifts in non-diversifiable risks, thus helps to explain why European investors remain significantly biased toward domestic assets (equity home bias).

The remainder of this chapter is structured as follows: [Section 1.2](#) reviews the related literature; [Section 1.3](#) describes the impact of data granularity on the interpretation of the correlation-based IDB measure and proposes alternative indicators; [Section 1.4](#) carries out an empirical study based on European stock markets; [Section 1.5](#) presents robustness tests; [Section 1.6](#) concludes.

## 1.2. Related literature

The standard approach to measure the benefits of international portfolio diversification is the mean-variance methodology. This method is based on a comparison of the risk-return profiles of two optimal portfolios. Following the work of Markowitz (1952), researchers draw efficient

frontiers from given sets of securities, representing the best asset combinations in terms of expected returns and risk. Using spanning tests, [De Roon et al. \(2001\)](#) compare the efficient frontiers of distinct baskets of domestic and international stocks and discover that US stockholders can substantially improve their portfolios by investing in emerging markets. However, the evidence is more limited when the authors control for transaction costs and short-sales constraints. [Driessen and Laeven \(2007\)](#) generalize the previous study for a large panel of countries. They highlight that, although diversification gains have decreased over time, most domestic investors can still benefit from investing abroad.

The mean-variance framework has some limitations. In particular, it is sensitive to variations or errors in the estimation of the input parameters ([Black and Litterman, 1991](#)). While variances and correlations can be computed quite precisely, expected returns are difficult to estimate ([Merton, 1980](#)). Furthermore, the mean-variance approach is a static framework, as it does not readjust the asset allocation over time. The methodology is thus poorly suited to analyze the long-term evolution of IDB. To tackle this issue, the literature suggests using the inverse of international stock return correlation as a simplified “correlation-based” IDB measure (see [Section 1.3](#)). This approach is suboptimal compared to the mean-variance methodology. Still, it tends to be more reliable for asset allocation, as it does not require the estimation of expected returns and variances ([Christoffersen et al., 2014](#)).

However, papers examining IDB based on the long-term evolution of stock market correlation tend to find contradictory results.<sup>1</sup> Beyond differences in sample, time frame, and methodology, we believe that studies yield conflicting findings depending on the type of underlying assets (i.e., country indices, domestic sectoral indices, or firm-level data). We summarize the main results of the papers that examine the dynamics of international stock return comovements in [Table 1.1](#).

Studies based on country indices usually indicate that the benefits of international diversification have decreased over time. [Longin and Solnik \(1995\)](#) show that there is a positive time-trend in the conditional correlation between seven advanced markets (1960–1990). Using data

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<sup>1</sup> Most of the studies merely state that the increase in the correlation among stock markets led to a decline in the benefits of international diversification. We follow [Christoffersen et al. \(2014\)](#) who use a dynamic IDB measure based on the inverse of international correlation among equity markets.

on 82 countries (1965–2008), Pukthuanthong and Roll (2009) document that stock market comovements have risen over time, especially within European countries, leading to a decline in IDB. Based on a sample of 16 developed and 13 emerging markets (1973–2012), Christoffersen et al. (2014) find evidence of an upward trend in international stock return correlation. Focusing on 32 emerging countries (1991–2009), Eiling and Gerard (2015) also note that emerging markets have become increasingly interdependent. Billio et al. (2017) compare the results based on different comovement measures for a sample of 27 markets (1973–2016). They find strong evidence of an increase in stock market interdependencies over time. Jordà et al. (2019) study the evolution of comovements among credit, house prices, and stock markets over the last 150 years for 17 countries. They emphasize that equity market interdependencies have sharply risen since the 1990s, reaching unprecedented levels. Bekaert and Mehl (2019) reach similar conclusions in their paper, indicating that stock market comovements followed a “swoosh” shape. One exception is the study of King et al. (1994), which does not find evidence of an upward trend in the correlation among 16 advanced stock markets (1970–1990).

On the other hand, studies based on local industry portfolios or firm-level data yield more mixed results. Kaltenhäuser (2002) shows that the correlation among domestic industry indices decreased from 1988 to 2002 within the euro area, the United Kingdom, and the United States. Carrieri et al. (2004) note that even fully integrated countries can have domestic industry portfolios segmented from the world market. Berben and Jansen (2005) assert that international correlation among domestic industry portfolios is lower than the comovements among country indices. They show that the interdependencies among country indices (Germany, Japan, the United Kingdom, and the United States) globally increased from 1980 to 2000. However, they find limited evidence of a rise in international correlation among local industries. Ratner and Leal (2005) reach the same conclusion based on the average comovements between the US industry indices and those of 37 developed and emerging countries (1981–2000). Kearney and Potì (2006) reveal that the correlation between 42 individual European stocks remained stable over the period 1993–2002, in contrast to the interdependencies between five European country indices. Focusing on 26 industry portfolios within 23 developed and emerging countries (1980–2005), Bekaert et al. (2009) find no evidence of an increase in comovements among industry portfolios. Interestingly, they do not detect an upward trend in the comovements among na-

tional indices either, except for European stock markets. Finally, Evans et al. (2017) confirm the findings of Berben and Jansen (2005) based on the G7 countries (2000–2013).

**Table 1.1.** Literature review

Papers	Time frame	Sample	Correlation dynamics		
			Country indices	Industry indices	Firm-level data
King et al. (1994)	1973–1988	16 advanced countries	Stable	n/a	n/a
Longin and Solnik (1995)	1960–1990	7 advanced countries	Rise	n/a	n/a
Kaltenhäuser (2002)	1988–2002	Europe & the US	Rise	Decrease	n/a
Berben and Jansen (2005)	1980–2000	4 advanced countries	Rise	Mixed results	n/a
Ratner and Leal (2005)	1981–2000	US with 37 countries	Rise	Mixed results	n/a
Kearney and Poti (2006)	1993–2002	European countries	Rise	n/a	Stable
Pukthuanthong and Roll (2009)	1973–2008	82 countries	Rise	n/a	n/a
Bekaert et al. (2009)	1980–2005	23 countries	Rise (in Europe)	Stable	n/a
Christoffersen et al. (2014)	1973–2012	29 countries	Rise	n/a	n/a
Eiling and Gerard (2015)	1991–2009	Emerging markets	Rise	n/a	n/a
Evans et al. (2017)	2000–2013	G7 countries	Rise	Mixed results	n/a
Billio et al. (2017)	1973–2016	27 countries	Rise	n/a	n/a
Jordà et al. (2019)	1870–2013	17 advanced countries	Rise	n/a	n/a
Bekaert and Mehl (2019)	1885–2014	17 advanced countries	Rise	n/a	n/a

*Notes:* This table reviews the papers that examine international correlation dynamics among countries, local industries, and individual securities. The articles are sorted in order of publication.

### 1.3. Methodology

The correlation-based IDB measure was introduced by Christoffersen et al. (2014). This section describes under which assumptions and prerequisites this *standard* approach can be considered as a suitable IDB measure. Then, we propose alternative indicators to address some of the drawbacks of the standard metric.

1.3.a. *Correlation-based measure: a simplified approach of diversification*

The correlation-based measure of the benefits of international diversification ( $IDB_t$ ) is based on Equation (1.1):

$$IDB_t = 1 - \rho_{avg,t}^{INT/GRAN} \quad (1.1)$$

in which  $GRAN = \{DOM, SECT, FIRM\}$ , i.e., country indices, local industry portfolios, or individual securities, represents data granularity, and  $\rho_{avg,t}^{INT/GRAN}$  stands for the average correlation between the components of the international portfolio at date  $t$ , such as

$$\rho_{avg,t}^{INT/GRAN} = \sum_i^H \sum_j^H w_{i,t} w_{j,t} \rho_{GRAN_i,GRAN_j,t}^{INT} \quad (1.2)$$

where  $\rho_{GRAN_i,GRAN_j,t}^{INT}$  is the correlation coefficient between assets  $i$  and  $j$  within the international portfolio at date  $t$ .  $w_{i,t}$  and  $w_{j,t}$  represent the weights of each asset within the international portfolio. IDB depend negatively on the degree of correlation among the components of the global portfolio (see Equation 1.1).

The correlation-based measure is a simplification of the mean-variance methodology ( $IDB_t^{MV}$ ), which compares the risk-return profiles between two (optimal) portfolios (e.g., the international portfolio and one of its components):

$$IDB_t^{MV} = 1 - \frac{R_{GRAN_i,t}/\sigma_{GRAN_i,t}^2}{R_{INT,t}/\sigma_{INT,t}^2} \quad (1.3)$$

in which  $R_{INT,t}$ ,  $R_{GRAN_i,t}$ ,  $\sigma_{INT,t}^2$ , and  $\sigma_{GRAN_i,t}^2$  represent the expected returns and variances of the international portfolio and its component  $i$ , respectively. The benefits of international diversification increase when the return-to-risk profile of the global portfolio rises compared to that of asset  $i$ . However, this approach is not properly suited for analyzing the evolution of IDB, as it requires expected returns, which are unknown, potentially unstable, and difficult to estimate.

We can circumvent this issue by comparing the risk-return profile of the international portfolio with that of its average component since both have the same expected returns:

$$R_{INT,t} = \sum_{i=1}^H w_{i,t} R_{GRAN_i,t} = R_{GRAN_{avg,t}}$$

where  $R_{GRAN_{avg,t}}$  stands for the returns of the average component of the global portfolio. Equation (1.3) can be simplified as follows:

$$IDB_t^V = 1 - \frac{\sigma_{INT,t}^2}{\sigma_{GRAN_{avg,t}}^2}$$

in which  $\sigma_{GRAN_{avg,t}}^2$  denotes the variance of the average component of the international portfolio. The closer the variance of the average asset is to that of the global portfolio, the smaller the IDB.

Under the assumption that all the components of the international portfolio have the same variance (equal variance hypothesis), the average (intra-portfolio) correlation is equal to the ratio of the variance of the global portfolio to that of the average asset (see Equation 1.5). We test the equal variance hypothesis empirically, based on 15 European stock markets (1973–2018), and show that it does not have a significant impact on the results in the long run (see Figure 1.4 in Appendix 1.1). Equation 1.5 is related to the “law of average covariance” (Markowitz, 1959), which states that, as the number of assets in a portfolio increases, the variance of an equally weighted portfolio tends toward the average covariance among its components. We rely on the equal variance hypothesis so that the equality also stands for capitalization-weighted and maximum diversification portfolios.

$$\sigma_{INT,t}^2 = \sum_{i=1}^H \sum_{j=1}^H w_{i,t} w_{j,t} \sigma_{GRAN_{i,t}} \sigma_{GRAN_{j,t}} \rho_{GRAN_{i,t}, GRAN_{j,t}}^{INT} \quad (1.4)$$

Under the assumption that  $\sigma_{GRAN_{i,t}} = \sigma_{GRAN_{j,t}} = \sigma_{GRAN_{avg,t}}$  for all  $i, j$ , Equation (1.4) becomes

$$\sigma_{INT,t}^2 = \sigma_{GRAN_{avg,t}}^2 \sum_{i=1}^H \sum_{j=1}^H w_{i,t} w_{j,t} \rho_{GRAN_{i,t}, GRAN_{j,t}}^{INT}$$

Then, based on Equation (1.2),

$$\begin{aligned} \sigma_{INT,t}^2 &= \sigma_{GRAN_{avg,t}}^2 \rho_{avg,t}^{INT/GRAN} \\ \rho_{avg,t}^{INT/GRAN} &= \frac{\sigma_{INT,t}^2}{\sigma_{GRAN_{avg,t}}^2} \end{aligned} \quad (1.5)$$

Hence, an increase in international (intra-portfolio) correlation leads to a decrease in the benefits of international diversification, defined as the gains of holding the global portfolio over the average component.

The correlation-based measure is more appropriate than the mean-variance methodology to analyze the long-term evolution of IDB (Section 1.2). However, since it is a simplified approach, correlation-based indicators have certain drawbacks. In most cases, the components of an international portfolio are heterogeneous, and the average asset is not always tradable. The correlation-based measure thus disregards the fact that some domestic investors may benefit more than others from investing abroad. Moreover, the method does not consider short sales, leverage, or other costs associated with foreign investments.

### 1.3.b. *The relative and absolute benefits of international diversification*

Based on domestic portfolios, the correlation-based IDB measure becomes

$$IDB_t^{Relative} = 1 - \rho_{avg,t}^{INT/DOM} = 1 - \frac{\sigma_{INT,t}^2}{\sigma_{DOM_{avg,t}}^2} \quad (1.6)$$

The average correlation between country indices ( $\rho_{avg,t}^{INT/DOM}$ ) compares the risk of a globally diversified portfolio to that of the average country index. Therefore, the IDB measure based on country indices estimates the relative gains of holding a global portfolio over the average domestic one. This relative gain is expressed as a percentage of the variance of the average local portfolio. The advantage of this measure is to provide investors with a dynamic metric that can help them decide whether to hold a global or the average local portfolio.

Based on firm-level data or domestic sectoral portfolios, the correlation-based IDB measure becomes

$$IDB_t^{Absolute} = 1 - \rho_{avg,t}^{INT/(SECT,FIRM)} = 1 - \frac{\sigma_{INT,t}^2}{\sigma_{(SECT,FIRM)_{avg,t}}^2} \quad (1.7)$$

The average correlation among individual stocks focuses on the benefits of holding a globally diversified portfolio over the average stock. In other words, it examines the absolute level of diversification within the international portfolio. While this method can compare the absolute benefits of investing internationally between different periods, it is of little practical interest for

investment decisions, as it does not help investors decide between holding a domestic or a global portfolio.

Although quite close in appearance, the previously detailed measures estimate the relative and absolute IDB, respectively. Different levels of data granularity thus impact the interpretation of IDB, which may contribute to explain some of the contradictory findings in the literature. These elements indicate that data granularity should be carefully selected according to research purposes.

### 1.3.c. A ratio-based IDB measure

A reliable IDB measure should guide investment decisions and shed light on the equity home bias puzzle. While the relative approach seems to be better suited to clarify this problem, it has several limitations. First, it can only be estimated using country indices. Second, the measure focuses on one type of investor, typically holding capitalization-weighted portfolios. Third, it fails to provide transparency about the underlying forces driving the benefits of international diversification.

Therefore, we propose an adjusted indicator (ratio-based measure), which scales the absolute IDB measure by the domestic diversification benefits (i.e., the gain of holding a country portfolio instead of the average asset). This approach can measure the relative benefits of international diversification regardless of the type of data granularity (i.e., country indices, domestic sectoral portfolios, or firm-level data). It also allows us to study IDB for different types of domestic investors holding equally weighted, capitalization-weighted, or maximum decorrelation portfolios. Finally, using more disaggregated data enables one to examine the forces driving the evolution of the relative IDB.

Using local industry portfolios or individual securities, we can develop Equation (1.6) by restating the variance formulas of the international and domestic portfolios. We reformulate the variance of the international portfolio following Equations (1.4) and (1.5). Similarly, we reprocess the variance of the average domestic portfolio as follows:

$$\sigma_{DOM_{avg},t}^2 = \sum_{k=1}^K w_{k,t} \sum_{i=1}^H \sum_{j=1}^H w_{i,t} w_{j,t} \sigma_{GRAN_i,t} \sigma_{GRAN_j,t} \rho_{GRAN_i,GRAN_j,t}^{DOM}$$

$$\sigma_{DOM_{avg,t}}^2 = \sigma_{GRAN_{avg,t}}^2 \rho_{avg,t}^{DOM/GRAN}$$

in which  $GRAN = \{SECT, FIRM\}$ , i.e., domestic sectoral indices or firm-level data, denotes data granularity,  $\rho_{avg,t}^{DOM/GRAN}$  represents the average correlation within the average domestic portfolio and,  $w_{k,t}$  is the weight of each domestic portfolio  $k$  within the international portfolio. The absolute level of the benefits of local diversification ( $DDB_t^{Absolute}$ ) can be written as

$$DDB_t^{Absolute} = 1 - \rho_{avg,t}^{DOM/GRAN} \quad (1.8)$$

Then, the average correlation among country indices becomes the ratio between international and local (intra-portfolio) comovements:

$$\rho_{avg,t}^{INT/DOM} = \frac{\sigma_{INT,t}^2}{\sigma_{DOM_{avg,t}}^2} = \frac{\sigma_{GRAN_{avg,t}}^2 \rho_{avg,t}^{INT/GRAN}}{\sigma_{GRAN_{avg,t}}^2 \rho_{avg,t}^{DOM/GRAN}} = \frac{\rho_{avg,t}^{INT/GRAN}}{\rho_{avg,t}^{DOM/GRAN}} \quad (1.9)$$

The ratio-based IDB measure ( $IDB_t^{Ratio}$ ) can be stated as

$$IDB_t^{Ratio} = 1 - \frac{\rho_{avg,t}^{INT/GRAN}}{\rho_{avg,t}^{DOM/GRAN}} \quad (1.10a)$$

Based on Equations (1.7) and (1.8), we can also formulate Equation (1.10a) as follows:

$$IDB_t^{Ratio} = 1 - \frac{1 - IDB_t^{Absolute}}{1 - DDB_t^{Absolute}} \quad (1.10b)$$

The adjusted IDB measure is based on the ratio between international and domestic (intra-portfolio) correlations. It can capture the relative gains of holding the global portfolio over the average country index regardless of data granularity. All else unchanged, the relative IDB decline (i) when the absolute level of *international* diversification drops or (ii) when the benefits of *domestic* diversification rise. Therefore, the ratio-based measure allows us to investigate the underlying forces driving IDB. Similarly, Equation (1.9) suggests splitting the rise in interdependencies among country indices into two components: (i) an increase in international comovements across firms or (ii) a decrease in domestic linkages between companies. As mentioned before, the advantage of this framework over previous approaches lies in its direct implications for asset allocation.

## 1.3.d. A spread-based IDB measure

The global systematic risk cannot be diversified and equally impacts the international and the average domestic portfolios. Non-diversifiable risks thus do not influence local investors' incentive to invest abroad. Hence, we argue that relative IDB measures should not consider the global systematic risk. However, we show that the standard and ratio-based IDB measures are not robust to shifts in non-diversifiable risks. In fact, any increase in the influence of global factors generates an equal rise in the variances of the global and average national portfolio, leading to a decrease in the relative IDB measure (i.e., ratio effect). Let us consider the following equation:

$$y_{i,t} = \alpha_i + \beta f_t + \varepsilon_{i,t}$$

where  $E[\varepsilon_{i,t}] = 0$ ,  $E[\varepsilon_{i,t}^2] < \infty$ , and  $E[f_t \varepsilon_{i,t}] = 0$ ;  $y_{i,t}$  represents the returns of the international and the average domestic portfolios, respectively; and  $f_t$  is an international factor that equally impacts the two portfolios. The variance of  $y_i$  depends on (a) the exposure to the international factor, (b) the variance of the international factor, and (c) an idiosyncratic component (see Equation 1.11).

$$\sigma_{y_{i,t}}^2 = \beta^2 \sigma_{f_t}^2 + \sigma_{\varepsilon_{i,t}}^2 \quad (1.11)$$

Based on Equations (1.9), (1.10a), and (1.11), we restate the relative IDB measure:

$$IDB_t^{Ratio} = 1 - \frac{\sigma_{\varepsilon_{INT,t}}^2 + \beta^2 \sigma_{f_t}^2}{\sigma_{\varepsilon_{DOM_{avg,t}}}^2 + \beta^2 \sigma_{f_t}^2}$$

Since the idiosyncratic part of the variance of the international portfolio is less than or equal to that of the average domestic one, an increase in the global systematic risk leads to a rise of the variance ratio.

$$\begin{aligned} \sigma_{DOM_{avg,t}}^2 &\geq \sigma_{INT,t}^2 \\ \left( \frac{\sigma_{INT,t}^2}{\sigma_{DOM_{avg,t}}^2} \right)^h &\geq \left( \frac{\sigma_{INT,t}^2}{\sigma_{DOM_{avg,t}}^2} \right)^l \\ \left( \frac{\rho_{avg,t}^{INT/SECT}}{\rho_{avg,t}^{DOM/SECT}} \right)^h &\geq \left( \frac{\rho_{avg,t}^{INT/SECT}}{\rho_{avg,t}^{DOM/SECT}} \right)^l \end{aligned}$$

$$(IDB_t^{Ratio})^h \leq (IDB_t^{Ratio})^l$$

in which the exponents  $h$  and  $l$  represent periods when the influence of the systematic risk is strong or low, respectively. Since the relative IDB measure is based on a correlation ratio (or a variance ratio), a rise in the global systematic risk would, all else unchanged, lead to a decrease in the ratio-based IDB measure. This finding is close to Forbes and Rigobon (2002), who show that the correlation coefficient between countries is not robust to heteroscedasticity.

As an alternative IDB measure, we propose to focus on the spread between domestic and international (intra-portfolio) correlations, such as

$$IDB_t^{Spread} = \rho_{avg,t}^{DOM/GRAN} - \rho_{avg,t}^{INT/GRAN} \quad (1.12a)$$

Based on Equations (1.7) and (1.8), we can also formulate Equation (1.12a) as follows:

$$IDB_t^{Spread} = IDB_t^{Absolute} - DDB_t^{Absolute} \quad (1.12b)$$

Unlike ratio-based measures, spread-based measures are robust to similar changes in the domestic and international (intra-portfolio) correlation.<sup>2</sup> This approach is expressed in percentage points (of correlation) rather than in percent increase. This new measure can be computed using local industry portfolios or firm-level data.

## 1.4. Empirical application

This section carries out an empirical study based on 15 European stock markets from 1973 to 2018. First, we compare the evolution of the inverse of international stock return correlation using three types of base assets (i.e., country indices, local industry portfolios, and individual stocks). Then, we investigate the evolution of the benefits of European diversification using the ratio-based IDB measure and test the consistency of the results against different data granularities and portfolio-weighting schemes. We also study the main underlying drivers of the relative

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<sup>2</sup> Note that the spread-based measure is not totally immune to changes in systematic risk because global factors do not have an identical impact on international and domestic (intra-portfolio) correlations. Nevertheless, the effect of shifts in non-diversifiable risks is largely mitigated. To further reduce the global factor bias in this new measure, we eliminate the diagonal from the average of the correlation matrix, as it makes the impact of systematic risk more significant on smaller and less granular portfolios. The main results are also robust to the inclusion of this diagonal (see Section 1.5).

benefits of European diversification, namely the absolute levels of European and domestic diversification. Finally, we present the results of our spread-based IDB measure, which is more robust to the impact of international factors than the ratio-based indicator. This application is of interest to European investors wishing to improve the return-to-risk profile of their portfolios by better understanding the sources of diversification benefits in the region.

#### *1.4.a. Data*

Our empirical analysis is based on weekly returns from 15 European stock markets (Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom) over the 1973–2018 period. European countries are an interesting case study since they have undergone a substantial economic and financial integration process. Moreover, the dynamics of the comovements among European markets received considerable attention, allowing us to compare our results with previous findings. Note that four countries are not members of the euro area (Norway, Sweden, Switzerland, and the United Kingdom), which permits us to check whether the inclusion in the monetary union affects the results (see Table 1.9; Appendix 1.4). Finally, we focus on a restricted sample (European rather than international markets) to limit computational complexity—which increases rapidly with the sample size, especially with firm-level data.

We use three types of granularity: country indices (i.e., aggregate domestic portfolios), local industry portfolios, and firm-level data. Each country index can be decomposed into ten domestic sectoral indices (subject to availability), which contain several firms (see Table 1.2). We use Datastream Global Equity Indices, which are built according to the FTSE-Dow Jones Industry Classification Benchmark. These indices are capitalization-weighted and include dividends. The Level 2 indices consist of the ten following sectors: Basic Materials, Consumer Goods, Consumer Services, Financials, Healthcare, Industrials, Oil&Gas, Technology, Telecommunications, and Utilities. Each index represents more than 75% of the market capitalization of the related country or sector. We use Datastream indices instead of those provided by local stock exchanges, as they are built according to a unique methodology. Moreover, there is no overlap between indices, as foreign listings are excluded from each index. As of 2018, our database includes 15 country indices, which consist of 141 domestic sectoral indices and 2,039

firms. For a given country, domestic data are included in our analysis as soon as at least five domestic sectoral indices and ten firms are available.

**Table 1.2.** Description of the data

Country index	Starting date	Number of sectors	Number of firms	Market capitalization (% of the sample)	
		as of 2018	as of 2018	as of 1990	as of 2018
Austria	1988	8	49	0.8	1.0
Belgium	1973	10	89	2.6	2.7
Denmark	1988	9	49	1.2	2.8
Finland	1988	10	50	0.8	1.8
France	1973	10	249	11.7	18.3
Germany	1973	10	249	17.6	15.2
Ireland	1973	8	37	0.7	0.8
Italy	1973	10	158	8.0	4.9
Netherlands	1973	9	123	7.3	5.5
Norway	1980	9	50	0.9	2.2
Portugal	1990	10	51	0.4	0.5
Spain	1987	10	117	5.1	5.3
Sweden	1982	9	70	2.1	4.3
Switzerland	1973	9	150	4.7	11.1
United Kingdom	1973	10	548	36.1	23.5
Total		141	2,039	100	100

*Notes:* We compare the market capitalization of the indices between 1990 (first observation for which all national indices are available) and 2018 (last observation available).

Three challenges emerge when dealing with stock market correlation: missing data, the non-alignment of time zones, and the differences of currencies. The existence of missing data, which stems from non-synchronized public holidays between countries, can bias the estimation of comovements among markets.<sup>3</sup> Financial markets also have different opening and closing hours, implying partial (or the absence of) overlapping trading hours. We fix these issues by calculating weekly returns, even though doing so induces a loss of observations and information compared to daily return calculations. We compute linear returns using averages of the daily closing prices for each week, instead of the more common Friday-to-Friday or Wednesday-to-Wednesday approaches. Returns based on means of daily closing prices are more representative of the events of the entire week, while the other methods suffer from a daily bias. Friday-to-Friday returns tend to be (i) less correlated with Wednesday-to-Wednesday returns than those based on average prices and (ii) more volatile than returns based on the two other methods

<sup>3</sup> Datastream deals with missing data by replacing each missing observation by the previous one, which preserves the size of the database.

(Baumöhl and Lyócsa, 2012). Besides, the returns based on average prices are tradable and represent the fact that investors tend to smooth their entry and exit points over time (here over a week). All the series are denominated in US dollars (including currency risk) to preserve data consistency and for realism purposes.<sup>4</sup>

The main diagnostic tests and descriptive statistics for the country and aggregate sectoral indices are presented in Table 1.3 (see Appendix 1.2). Results for domestic sectoral indices and firm-level data are not included but are available from the author upon request. The statistics are based on weekly returns from 1973 to 2018 (2,345 observations). The results highlight that the distribution of returns is leptokurtic and asymmetric. They also underline the presence of outliers that might bias standard correlation estimators. Consequently, we estimate stock market correlation based on an outlier-robust method (i.e.,  $Q_n$  estimator).

#### *1.4.b. Estimation procedure*

We use an unconditional correlation estimator, computed dynamically on a rolling window basis, with partially overlapping data. Unconditional estimation methods do not require assumptions about the correlation dynamics. They are also better suited for high-dimensional settings and enable one to handle missing data by progressively including the series when data become available. Since the traditional estimators of correlation (e.g., Pearson correlation) have poor resistance to data contamination (e.g., outliers and non-normality), we use the efficient and outlier-robust  $Q_n$  estimator (for details, see Appendix 1.1). This estimator is not standard in the finance literature, so we check whether the use of Spearman's nonparametric correlation coefficient leads to similar conclusions.

Other approaches, which assume a specific form in the dynamics of the conditional covariance matrix, may be better suited to tackle data heteroscedasticity. However, these approaches are more prone to modeling errors and convergence issues. Moreover, different methods of estimating correlation lead to similar results in the long run (Billio et al., 2017).

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<sup>4</sup> We use prices denominated in dollars rather than in euros because (i) our selection is not limited to the euro area, (ii) the euro was introduced in 1999, while our sample covers the period 1973–2018, and (iii) our factor analysis includes global factors traditionally denominated in dollars.

There is no method to determine the optimal length of the rolling window. The window must be wide enough to estimate precise parameters and short enough to avoid smoothing out important evolutions. Lewellen and Nagel (2006) argue that short windows provide conditional parameters without the need to specify conditioning information, as long as the coefficients are relatively stable within the window. It is also essential to consider that information might come at various frequencies and have different degrees of persistence in financial markets. Our main results are estimated using weekly returns and a one-year window. We perform a robustness test by examining the dynamics of IDB based on (i) a two-year window and (ii) monthly returns (see Section 1.5).

#### *1.4.c. Results*

We estimate IDB dynamically, according to the previously detailed methodology, and treat the resulting time series as observable.

##### *i. The impact of data granularity on the standard IDB measure*

We compare the evolution of the benefits of European diversification based on the standard measure (i.e., the inverse of the correlation among European stock markets) from 1974 to 2018 using different types of data granularity (see Figure 1.1). The results indicate that, on average, the benefits of European diversification based on domestic sectoral indices and firm-level data are higher than those based on country indices (64.0%, 77.4%, and 41.2%, respectively; see Table 1.4 in Appendix 1.3). This finding is consistent with the fact that the variance of the average firm is less than or equal to that of the average domestic industry or country index (see Equations 1.6 and 1.7).

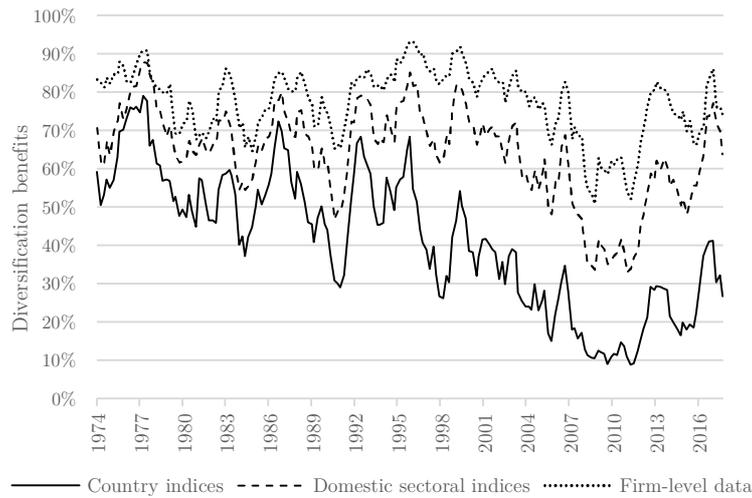
Then, we test for deterministic trends in the diversification series to examine if the benefits of European diversification have significantly decreased over time. The diagnostic tests, presented in Table 1.4, indicate that the assumptions of unit root and autocorrelation are not rejected. Therefore, we run robust linear trend tests introduced by Bunzel and Vogelsang (2005) and Perron and Yabu (2009a), which are valid with  $I(0)$  or  $I(1)$  errors. They propose an adjustment to account for the problem of over-rejection in the standard trend tests. Bunzel and Vogelsang (2005) apply a correction factor to the test statistic based on the results of a unit

root test, such that the limit distribution under the null hypothesis is the same whether the noise is  $I(0)$  or  $I(1)$ . Due to the scaling factor, the t-statistics depend on the significance level of the test. It is standard practice in the literature to report the t-statistics associated with the 5% critical value for the one- and two-tailed tests ( $t_{10\%}$  and  $t_{5\%}$ , respectively) because the most likely alternative hypothesis is that IDB have decreased over time (see Bekaert et al., 2009). On the other hand, Perron and Yabu (2009a) use a Feasible Quasi Generalized Least Squares method. Based on this approach, inference on the slope coefficient can be measured using the standard Normal distribution in the  $I(0)$  and  $I(1)$  cases. The test of Bunzel and Vogelsang (2005) has better size control but relatively low power properties compared to Perron and Yabu (2009a) in finite samples and in the exact  $I(1)$  environment. We also test for nonlinear deterministic trends based on Perron et al. (2017). Building on Perron and Yabu (2009a), this test is valid regardless of the order of integration of the series. Their approach relies on a Fourier expansion with an arbitrary number of frequencies that can fit a large class of nonlinear trends. As far as we know, our study is the first to control for non-linear trends in stock market correlation and diversification series.

Based on Bunzel and Vogelsang (2005), we find strong evidence that the benefits of European diversification based on country indices significantly decreased from 1974 to 2018 ( $-1\%$  annually; see Table 1.5 in Appendix 1.3). By contrast, there is no such evidence for the benefits of European diversification based on local industry indices and individual securities. Overall, it appears that the test of Perron and Yabu (2009a) is more conservative than that of Bunzel and Vogelsang (2005). Moreover, none of the series exhibit nonlinear deterministic trends according to the test of Perron et al. (2017) with a frequency set at one. As shown in Section 1.3, estimating correlation among country indices generates a *relative* IDB measure, whereas calculating comovements among domestic sectoral portfolios and firm-level data captures *absolute* IDB. Our results thus reveal that the relative IDB have significantly declined over time, indicating that local investors have fewer incentives than before to invest in other European countries. This finding may explain why European investors remain significantly biased toward domestic assets (equity home bias; see Table 1.8 in Appendix 1.4).

On the other hand, the slight decrease in the absolute level of European diversification (by  $-0.4\%$  and  $-0.2\%$  per year for local industry indices and individual securities, respectively)

mainly resulted from transitory shocks. In 2018, the absolute IDB was almost unchanged from 1974, meaning that investors who hold European portfolios have not become less diversified over time. This finding is counter-intuitive, as the increase in firms' international activities should lead to a permanent rise in comovements among the stock prices of European firms (e.g., Longin and Solnik, 1995). Furthermore, how can European investors have fewer incentives to invest in other European countries if the absolute IDB have remained roughly stable in the long run? We examine these puzzles in the following sub-sections.



**Figure 1.1. European diversification benefits based on the standard IDB measure**

This figure compares the evolution of the benefits of European diversification based on (i) country indices (solid line), (ii) domestic sectoral indices (dashed line), and (iii) firm-level data (dotted line). These results are based on equally weighted portfolios and estimated using one-year rolling windows.

*ii. The ratio-based IDB measure*

Using the ratio-based IDB measure, we reexamine the dynamics of the relative benefits of European diversification from 1974 to 2018. Figure 1.5 presents the results based on country indices, domestic sectoral portfolios, and firm-level data (see Appendix 1.3). Note that the standard and ratio-based measures using country indices are the same. On average, the relative IDB based on country indices, domestic sectoral indices, and firm-level data amount to 41.2%, 39.4%, and 34.7%, respectively (see Table 1.4). This discrepancy is limited compared to that based on the standard measure (see the previous sub-section).

Figure 1.5 shows that the estimates of the European diversification benefits based on the adjusted measure follow similar patterns, regardless of the granularity of base assets. All of the series exhibits significant linear downward deterministic trends (see Table 1.5), confirming that

the relative IDB have declined permanently over the past four decades. Moreover, data granularity does not impact the slope of the trend ( $-1\%$  per year on average). Hence, while the choice of base assets strongly affects the standard IDB measure, its influence on the ratio-based indicator seems to be negligible in the long run.

To complement this analysis, we examine (i) how different types of data granularity might have affected the findings of previous studies and (ii) whether our ratio-based IDB measure can help reconcile some of the conflicting results in the existing literature (see Table 1.6; Appendix 1.3). The analysis consists of selecting articles studying European stock market correlation, among other countries. We perform trend tests on the standard and ratio-based IDB series—obtained from our sample of European markets—over the time frame of the selected papers. This approach also enables us to check the consistency of the results over different periods.

Pukthuanthong and Roll (2009), Christoffersen et al. (2014), and Billio et al. (2017) find an increase in interdependencies among country indices over the periods 1974–2008, 1974–2012, and 1974–2016, respectively. While we confirm their findings based on country indices, we show that different types of data granularity would have led to conflicting results. By contrast, the ratio-based measure yields consistent conclusions regardless of the choice of base assets.

We also replicate the results of Bekaert et al. (2009), who report that the correlation among European country indices increased over the period 1980–2005. By contrast, the comovements among industry portfolios remained roughly stable. Interestingly, our findings indicate that the correlation among individual securities significantly declined over the same time frame. Again, the ratio-based measure leads to consistent results even though the trend test based on the interdependencies among firms is not significant at the 10% level (two-sided test).

Berben and Jansen (2005) and Evans et al. (2017) show that, while the correlation among country pairs globally increased over the periods 1980–2000 and 2000–2013, only some of the local industries became more integrated over time. We note that the interdependencies among country indices seem to have increased over time. However, we find no evidence of a deterministic upward trend. This discrepancy may result from the fact that our sample differs significantly from theirs. Finally, King et al. (1994) do not find evidence of a rising trend in the correlation among 16 stock markets from 1970 to 1990. We confirm this conclusion using both the standard and adjusted measures of IDB, regardless of the type of data granularity.

To summarize, our analysis suggests that data granularity needs to be carefully selected according to the research question, as it has a significant impact on international stock market correlation and the standard IDB measure. Based on country indices, the standard indicator always indicates a decline in IDB—and some evidence of a significant downward deterministic trend. By contrast, there is no such evidence based on more disaggregated data. Our results also highlight that, in most cases, the ratio-based IDB measure is robust to different types of base assets, allowing us to reconcile some of the mixed findings in the literature.

*iii. IDB for various kinds of investors*

The ratio-based approach can assess the benefits of international diversification for several types of investors. While some investors hold capitalization-weighted portfolios, others prefer to equalize weights or maximize portfolio decorrelation by weighting the least correlated sectors—or firms—more favorably. We test the robustness of the results to different portfolio-weighting schemes when calculating the average correlation among the components of the international and domestic portfolios (see Equation 1.2 in Section 1.3.a):

- equally weighted average, where  $w_{i,t} = w_{j,t} = \frac{1}{H}$ , with  $H$  representing the number of components of the portfolio;
- capitalization-weighted average, in which  $w_{i,t} = \frac{Mktcap_{i,t}}{Mktcap_{PORT,t}}$ , with  $Mktcap_{i,t}$  and  $Mktcap_{PORT,t}$  denoting the market capitalizations of component  $i$  and the portfolio under consideration at date  $t$ , respectively;
- maximum decorrelation average, as suggested by Christoffersen et al. (2014), where  $w_i = w_i^*$ ,  $w_j = w_j^*$ . In this case, the weights are estimated using an optimization procedure that minimizes the average correlation within the portfolio. This procedure enables one to weight highly diversifying assets (which are not strongly linked with the other securities) more favorably than lowly diversifying assets. We use a heuristic estimation method, as proposed by Varadi et al. (2012), instead of the traditional optimization procedures that are not robust against estimation errors in the correlation matrix. The heuristic method is a proportional weighted approach based on the ranks of the correlation coefficients. It enables us to maximize the target (portfolio decorrelation) while limiting the impact of the estimation errors. For example, instead of investing only in

the least correlated assets, this heuristic algorithm ensures diversification across the entire investment set.

Figure 1.6 represents the dynamics of the relative benefits of European diversification based on equally weighted, capitalization-weighted, and maximum decorrelation portfolios (see Appendix 1.3). The results are based on the adjusted measure using domestic sectoral portfolios. We obtain similar findings based on country indices and firm-level data. We show that stockholders relying on equally weighted or maximum decorrelation strategies have higher relative IDB than those with market-value portfolios (47%, 39%, and 32%, respectively; see Table 1.4). However, we provide evidence that all series follow significant linear deterministic trends, confirming that the relative benefits of European diversification decreased from 1974 to 2018. Our main results are thus robust to different portfolio-weighting schemes (see Table 1.5).

Furthermore, we note that the spread between the equally weighted and maximum decorrelation IDB significantly widened from 1974 to 2018 (+0.2% annually), suggesting that investors can partially offset the downturn in the relative IDB by overweighting the least integrated sectors in their portfolios. To examine this result in further detail, we look at the weight given to each sector within the maximum decorrelation portfolio. We find that maximum decorrelation portfolios favor technology, telecommunications, and utilities sectors, while capitalization-weighted portfolios are biased toward financial, consumer goods, and industrial sectors (see Figure 1.8 in Appendix 1.4). Using deterministic trend tests, we also show that the importance of the industrial and technology sectors significantly decreased from 1974 to 2018 (see Table 1.5). By contrast, the weight of the basic materials industry significantly rose over the same period, meaning that this sector has become more attractive for diversification purposes. These findings support those of Carrieri et al. (2004), who note that some local industries have grown more integrated than others (see Section 1.2). Therefore, investors can benefit from the fact that the integration process across sectors has been heterogeneous.

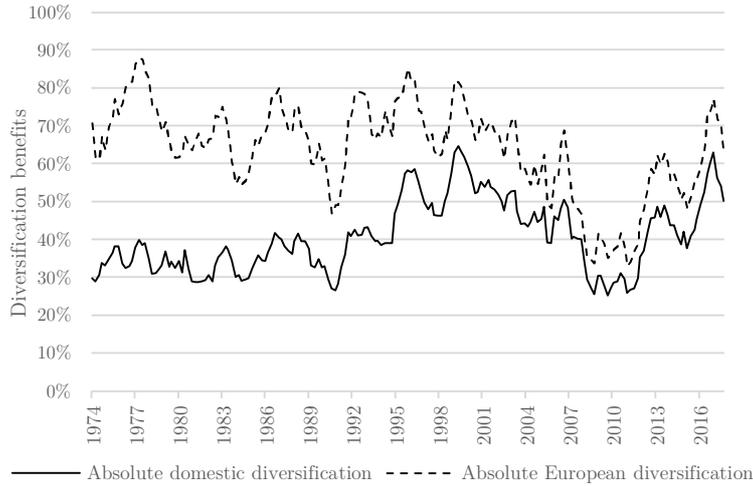
#### *iv. Underlying forces driving IDB*

The ratio-based measure provides a decomposition of the underlying forces driving the evolution of the relative IDB. As indicated above, the relative IDB decrease (i) when the absolute level of European diversification declines or (ii) when domestic diversification increases (see

Equation 1.10b). Our approach thus complements the papers of Pukthuanthong and Roll (2009) and Eiling and Gerard (2015) by introducing an alternative way of explaining the evolution of the relative IDB. Figure 1.2 describes the dynamics of the absolute levels of European and domestic diversification from 1974 to 2018. The results are based on domestic sectoral indices and are consistent with those based on firm-level data.

We find that the absolute level of European diversification is, on average, higher than domestic diversification (64% against 41% over the whole period; see Table 1.4). More importantly, European and domestic diversifications seem to have converged over time, especially during the 1990s (i.e., the spread between the absolute benefits of European and local diversification has reduced). The primary driver of this convergence is the increase in domestic diversification in the 1990s (see Figure 1.2). Indeed, the absolute level of local diversification doubled between 1974 and 2000 (from 30 to 60%), while the total level of European diversification remained at 70%. After this date, European and local diversifications tend to move in lockstep. As a result, in 2018, local investors benefited from higher domestic diversification than in 1974, whereas the total level of European diversification had remained roughly stable. This result indicates that investors' incentive to invest in foreign assets has decreased over time, which is due to the rise in the benefits of domestic diversification.

These findings also shed light on the impact of economic and financial integration on international comovements among domestic sectors and firms. Through their exports and foreign implantations, many firms have become internationally diversified. Unexpectedly, this process has not led to a significant increase in the linkages among individual securities at the European scale (see Table 1.5). Instead, we find some evidence that companies have become less correlated with other national firms. While there is no significant deterministic upward trend in domestic diversification from 1974 to 2018 (+0.3% annually), our factor analysis indicates that European firms have become durably less exposed to local shocks (see next sub-sections).



**Figure 1.2. European and domestic diversification benefits in absolute terms**

This figure presents the evolution of the absolute benefits of domestic (solid line) and European (dashed line) diversification. These results are based on domestic sectoral indices and equally weighted portfolios and are estimated using one-year rolling windows.

v. *The spread-based IDB measure*

As mentioned in [Sections 1.3.d](#), the global systematic risk influences the standard and ratio-based IDB measures. We argue that a reliable IDB measure should capture the ability to reduce diversifiable risk and should not be affected by the level of non-diversifiable risk. Indeed, non-diversifiable risks have an identical impact on the average domestic and international portfolios, so they do not influence local investors' incentive to invest abroad.

To deal with this bias, we propose a new measure of the relative IDB based on the spread between the absolute levels of European and domestic diversification benefits (see [Equation 1.12b](#)). This indicator is robust to a common increase in international and domestic (intra-portfolio) correlations (see [Section 1.3.d](#)). In the ratio-based measure, IDB are expressed in percent increase. By contrast, the spread-based indicator estimates the benefits of investing abroad in percentage points (of correlation). [Figure 1.3.](#) displays the evolution of the relative IDB using this alternative approach for firm-level data and local industry indices.

The findings confirm that the relative IDB have significantly decreased over time ( $-0.8\%$  and  $-0.5\%$  per year, based on industries and firms, respectively; see [Table 1.5](#)). Then, we compare the patterns of the relative IDB using the ratio- and spread-based indicators (see [Table 1.7](#); [Appendix 1.3](#)). First, we test for structural breaks in the slope and intercept of the trend function following [Perron and Yabu \(2009b\)](#). They propose a test for shifts in trend, which is

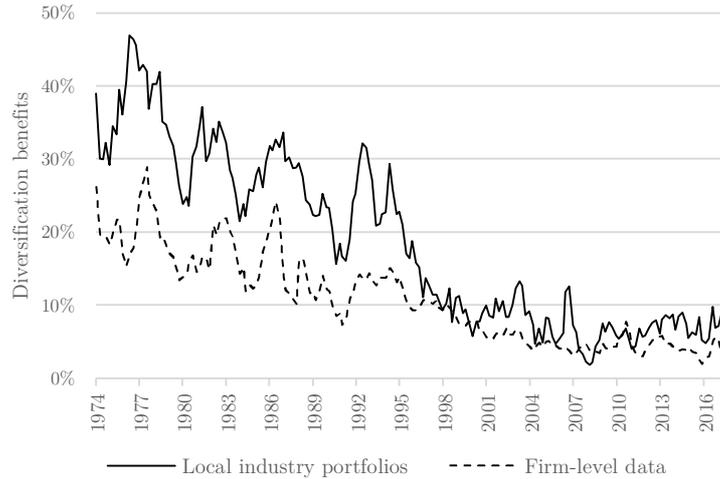
valid with an integrated or stationary noise component. The break dates are detected by minimizing the sum of squared residuals from regressions of IDB series on a constant, a time trend, a level-shift dummy, and a slope-shift dummy. Second, we run additional trend tests for the resulting sub-periods.

Using the ratio-based indicator, we find that IDB decreased from 1974 to 2008 before rebounding at the end of the period.<sup>5</sup> This finding is consistent with previous studies (e.g., [Evans et al., 2017](#)). However, structural breaks are not significant at the 5% level. By contrast, using the spread-based indicator, we find evidence that the intercept and the slope of the trend changed around the year 2000. This result indicates that the relative IDB mostly declined from 1974 to the late 1990s and did not recover (2000–2018). Therefore, the spread-based indicator sheds a different light on the dynamics of IDB in recent decades. Specifically, it reveals that domestic investors in Europe had already lost most of the incentive to invest in the rest of the region by the end of the 1990s.

These divergent patterns can be explained by the fact that, unlike the standard and ratio-based IDB measures, the spread-based indicator is robust to similar changes in the absolute levels of international and domestic diversification (see [Section 1.3.d](#)). Since the end of the 1990s, international and domestic diversifications have changed substantially but mostly in a synchronized fashion (see the previous sub-section and [Figure 1.2](#)). While the absolute levels of foreign and domestic diversification decreased from 2000 to 2010—impacting the standard and ratio-based IDB measures—the spread between them remained broadly unchanged, which explains the stability of the spread-based IDB measure. We assume that similar changes in international and domestic diversifications stem from variations in the global systematic risk. We explore this hypothesis in the next sub-section.

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<sup>5</sup> This is true for the measures based on country indices and local industry portfolio. The measure based on firm-level data present a different pattern. One possible reason is that the systematic risk bias is weaker for firm-based measures. Indeed, the average level of correlation between firms is lower, which reduces the impact of a similar increase in the numerator and denominator on the value of the ratio.



**Figure 1.3. European diversification benefits using the spread-based IDB measure**

This figure examines the dynamics of the relative benefits of European diversification using the spread-based IDB measure. The results are based on (i) domestic sectoral indices (solid line) and (ii) firm-level data (dashed line). We use equally weighted portfolios and one-year rolling windows.

*vi. Factor analysis*

We conduct a factor analysis, which provides additional insights into the determinants of the decline in the relative IDB. It also helps explain the diverging patterns between the ratio- and spread-based IDB indicators. Specifically, we examine the influence of the country, industry, and international factors on asset returns. We assume that country and industry factors impact both the ratio- and the spread-based IDB measures.<sup>6</sup> However, unlike the ratio-based indicator, our spread-based measure is robust to international factors (see Section 1.3.d).

A large body of literature examines the risk factors affecting the cross-section of stock returns. While previous papers focus primarily on whether investors should diversify across countries or global industries, some of their findings may help explain ours. Based on a sample of 12 European countries, [Heston and Rouwenhorst \(1994\)](#) highlight that industry factors only explained a small proportion of stock return variations compared to country factors. This finding is consistent with the fact that the relative IDB remain large at the beginning of the 1990s (see [Figure 1.3](#)). More recent studies show that the importance of the country factors relative to the industry factors declined at the end of the 1990s. [Phylaktis and Xia \(2006\)](#) note that, although the influence of the industry factors increased in 1999, particularly in Europe and North Amer-

<sup>6</sup> Country loadings influence positively the absolute benefits of domestic diversification. By contrast, global industry exposures have a negative impact on the absolute benefits of European diversification.

ica, it remained lower than that of the country factors. By contrast, Eiling et al. (2012) highlight that industry factors have outweighed country factors for European stocks in the post-Euro period. These findings may be at the root of the convergence of the absolute benefits of domestic and European diversification.

To test this hypothesis, we examine how country, industry, and international factors influence stock returns based on our set of domestic sectoral indices. The analysis is based on a multifactor asset-pricing model with time-varying factor loadings and time-varying factor volatilities. The approach consists of regressing the returns of each local industry portfolios on a set of five factors representing country, industry (regional and global), and international (regional and global) shocks, following Equation (1.13).

$$R_{i,t} = \alpha_i + \sum_{j=1}^5 \beta_{i,j} F_{i,j,t}^\perp + \varepsilon_{i,t} \quad (1.13)$$

in which  $R_i$ , a  $(T \times 1)$  vector, represents the returns of the local industry index  $i$ ;  $T$  is the number of observations;  $\alpha_i$  is the intercept; and  $F_{i,j}^\perp$  is a  $(T \times 5)$  matrix containing the orthogonalized factors (following the methodology described in Chapter 3; Appendix 3.1).  $\beta_{i,j}$  are the factor loadings, and  $\varepsilon_i$  represents the model errors. Factors and residuals are uncorrelated. For each regression, we address the concern of endogeneity by using a specific set of factors that exclude  $R_i$ . Then, based on a variance decomposition framework, we estimate the proportion of the variance of the local industry indices explained by each factor (variance ratio). For each factor, we report the cross-sectional averages among domestic industries.

We analyze the evolution of the variance ratios from 1974 to 2018 (see Figure 1.7 in Appendix 1.3). On average, over the whole period, the variance ratios associated with the country, industry (regional and global), and international (regional and global) factors are equal to 18%, 8%, and 35%, respectively (see Table 1.4). By dividing the sample into two equal sub-periods (1974–1997 and 1997–2018), we note that the influence of the country factors was dominant during the first sub-period (29% against 5% and 27% for industry and international factors, respectively), while it became weaker than those of the industry and international factors during the second sub-period (7%, 11%, and 43%, respectively). This finding is consistent with Eiling et al. (2012), suggesting that investors should now focus on diversifying into global industries rather than countries.

The results also indicate that the effect of the international and industry factors has increased over time (+0.7 and +0.2% annually), whereas the impact of the country factors has declined (−0.8% annually). Interestingly, only the variance ratios associated with the country and the industry (regional) factors exhibit significant deterministic trends (see Table 1.5, Panel C). This finding confirms that companies have become durably less exposed to domestic shocks. Conversely, the influence of the international (global) factor reached unprecedented levels over the past decade, before declining in recent years. This outcome could be due to the transitory impact of the global financial crisis (2007–2009) and the European debt crisis (2010–2012). As a result, we do not detect a deterministic upward trend in the international (global) factor effect.

The weakening of country factors during the 1990s led to an increase in the absolute benefits of domestic diversification. The sudden strengthening of industry factors in 1999 caused a slight reduction in the absolute benefits of European diversification. Taken together, these effects can explain the convergence of European and domestic diversifications during the 1990s, leading to a permanent decline in the spread-based IDB measure. Importantly, we point out that the influence of the international factors rose during the 2000s and declined in the 2010s, in line with the evolution of the standard and ratio-based IDB measures (see Figure 1.7). By contrast, the spread-based IDB measure does not reflect the dynamics of international factors. This finding implies that changes in the global systematic risk between 2000 and 2018 are at the root of the diverging patterns of the ratio- and spread-based indicators.

## 1.5. Robustness tests

We check whether the exclusion of some countries affects our results. First, we examine if IDB have experienced the same pattern in euro area countries as in other European countries. We divide our sample into two groups (i.e., eurozone and non-eurozone members), recompute the ratio- and spread-based IDB measures within each group, and run trend tests on the resulting series (see Table 1.9; Appendix 1.5). We do not display the firm-based results for non-eurozone countries because UK companies account for the bulk of the sample, so the firm-based IDB mostly capture domestic diversification benefits. We find that both groups have experienced a

similar decline in their relative IDB, suggesting that there is no specific pattern in the correlation among eurozone members.

Second, we control if our findings are distorted toward a single country. We successively re-estimate the relative benefits of European diversification by excluding, at each iteration, one of the 15 country indices included in the European portfolio. The analysis focuses on capitalization-weighted IDB measures, which are more likely to be biased toward the largest countries (see Table 1.2). The outcome of this robustness test consists of 15 series representing the relative benefits of European diversification based on a portfolio comprising 14 domestic indices. For each series, we perform additional trend tests (presented in Table 1.9) and confirm that the relative benefits of European diversification have significantly decreased over time. Therefore, the main results are robust to the exclusion of any country.

Then, we examine the impact of the size of the rolling window on the results. To this end, we compare the evolution of the relative IDB based on one- and two-year rolling windows, respectively (see Table 1.10; Appendix 1.5). As anticipated, the ratio- and spread-based IDB series are more volatile using a one-year rather than a two-year window. However, both series tend to follow similar long-term trends, confirming that the size of the window does not deeply impact the long-term dynamics of the results.

We also control that our findings are robust to different data frequencies. We compare IDB based on weekly returns (initial measure) with estimates based on monthly data (see Table 1.10). We confirm that both the ratio- and spread-based IDB follow a significant downward trend using monthly returns, indicating that data frequency does not significantly influence the results.

To test the robustness of the estimation method, we compare the results based on  $Q_n$  correlation with the Spearman estimator, a non-parametric measure of comovements based on ranks. The results show that the IDB measures follow similar patterns over time, confirming the robustness of our findings to different unconditional correlation estimators (see Table 1.10). Another method is to measure the ratio-based IDB using variance instead of correlation (see Appendix 1.1 and Equation 1.9). This approach allows us to relax the equal variance hypothesis. Again, we confirm that our main results are robust to this alternative specification.

Finally, we check whether the inclusion of the matrix diagonal in the average correlation impacts the relative IDB measures (see Equation 1.2). Unsurprisingly, we find that the diagonal tends to bias the average correlation coefficient upwards. This bias is likely to be larger for small portfolios or portfolios based on aggregate assets. Thus, we compare the dynamics of the relative IDB with and without including the diagonal (see Table 1.10). We find that the slope of the trend associated with ratio-based measure gets steeper when we exclude the diagonal. In any case, the analysis confirms that the relative IDB measures have significantly decreased over time.

## 1.6. Conclusion

Economic and financial integrations may have gone hand in hand with increasing international stock return correlation, leading to a decline in the benefits of international portfolio diversification. However, studies investigating this issue yield conflicting findings.

Our contributions to the literature are both methodological and empirical. First, we suggest that different data granularities might explain some of the mixed results in previous studies. We test this hypothesis by examining the dynamics of European stock market correlation (1974–2018) for different types of base assets (e.g., country indices, local industry portfolios, and individual securities). We find that, while the correlation among country indices has significantly increased over time, there is no such evidence for the comovements among local industry indices or individual securities. Interestingly, our findings suggest that the integration process has not led the stock prices of European companies to become more interdependent but has made them more resilient to domestic shocks. Consequently, we show that the decline in the *relative* IDB—highlighted by many studies—partly stems from the rise in the benefits of domestic diversification. Our analysis thus highlights the bright side of the decline in the relative IDB.

Second, based on the framework proposed by Christoffersen et al. (2014), we develop alternative IDB indicators that tackle some of the shortcomings of the standard correlation-based IDB measure. In particular, we construct a measure that is robust to changes in non-diversifiable risks. Based on this spread-based indicator, we shed new light on the evolution of

the relative IDB. While the standard measure indicates that European diversification benefits decreased from 1974 to the end of the 2000s before rebounding in the 2010s, our new indicator reveals that IDB declined from 1974 to the late 1990s and did not recover. This finding helps to explain why European investors remain significantly biased toward domestic assets (equity home bias). We rely on future research to determine whether our results can be generalized to other developed and emerging markets.

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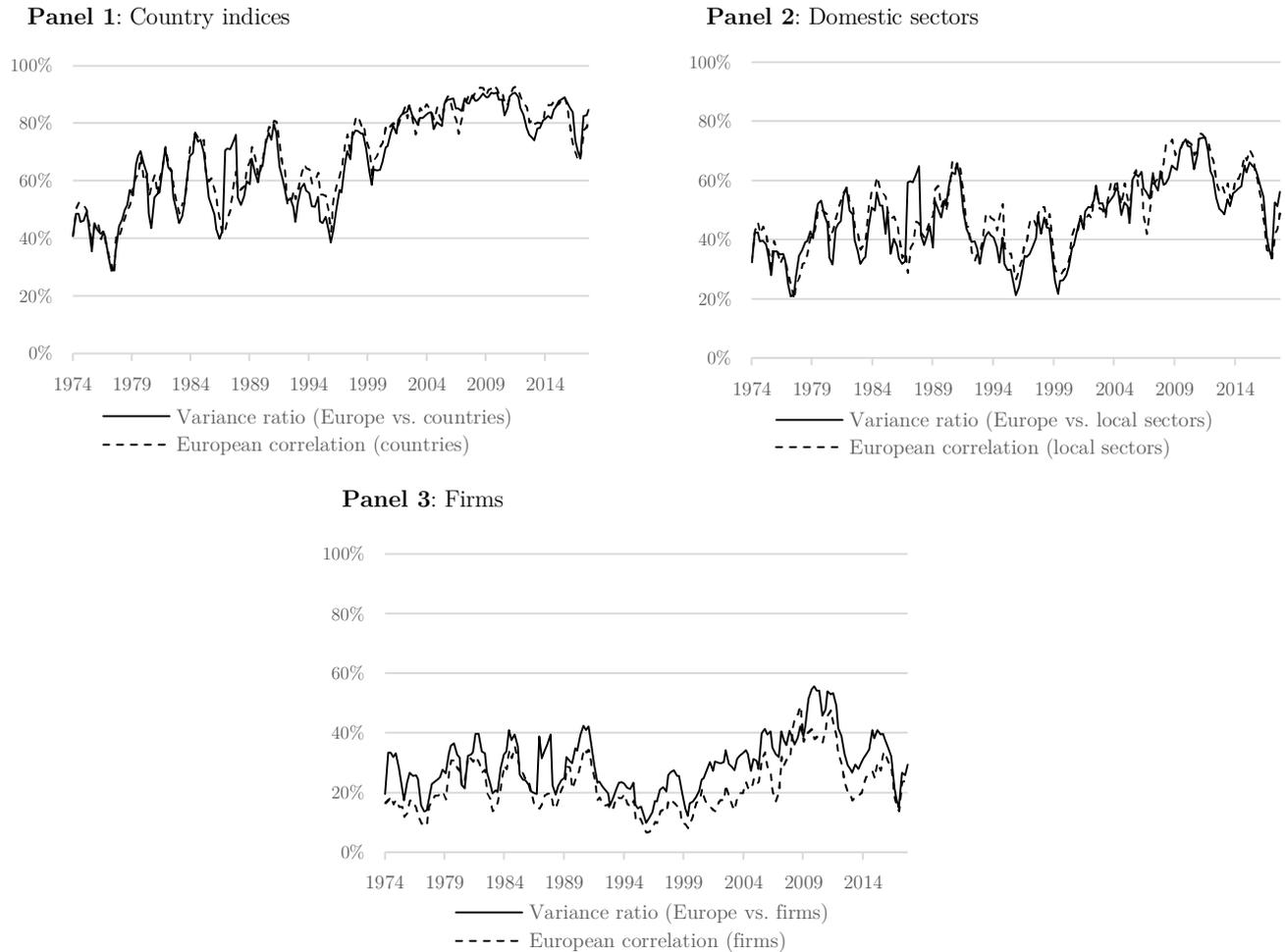
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## Appendices

### Appendix 1.1. Methodology

#### *A. Assumption behind the correlation-based measure of IDB*



**Figure 1.4. Empirical test of the equal variance hypothesis**

This figure compares the evolution of (i) the ratio of the variance of the European portfolio to that of the average country portfolio (solid line) and (ii) the average correlation within the components of the European portfolio (dashed line). Panel 1, 2, and 3 focus on country indices, local industry indices, and individual securities, respectively. The results are estimated using one-year rolling windows.

### B. $Q_n$ correlation estimator

The Pearson correlation coefficient has poor resistance to data contamination (e.g., outliers and non-normality). As a result, several outlier-robust correlation estimators have been proposed. In this chapter, we use the  $Q_n$  correlation coefficient, which is based on the following identity (Gnanadesikan and Kettenring, 1972):

$$\rho_{X/Y} = \frac{\sigma_U^2 - \sigma_V^2}{\sigma_U^2 + \sigma_V^2}$$

with  $\rho_{X/Y}$  the correlation coefficient between the variables  $X$  and  $Y$ ,  $U = (X/\sigma_X + Y/\sigma_Y)/\sqrt{2}$  and  $V = (X/\sigma_X - Y/\sigma_Y)/\sqrt{2}$ . The resulting correlation matrix needs to be orthogonalized following Maronna and Zamar (2002) to ensure that it is positive semi-definite.

By choosing a robust estimator of scale instead of the standard deviation, we obtain an estimator of correlation that is more robust to data contamination than Pearson correlation. We use the  $Q_n$  estimator, which is an efficient and robust estimator of scale proposed by Rousseeuw and Croux (1993) based on the pair-wise absolute differences between observations:

$$Q_n(x) = c\{|x_i - x_j|; i < j; i, j = 1, 2, \dots, n\}_{(k)}$$

where  $x = (x_1, \dots, x_n)^T$  is a sample of a random variable  $X$ , with  $n$  the number of observations,  $k = \binom{h}{2}$  with  $h = n/2 + 1$ , and  $c = 2.2191$  representing a constant chosen to provide consistency of estimation with the standard deviation of a normal distribution. This approach sorts the absolute differences  $|x_i - x_j|$  in increasing order and selects the  $k^{\text{th}}$  order statistic of the  $\binom{n}{2}$  interpoint distance.

Rousseeuw and Croux (1993) argue that this measure should be used instead of the median of absolute deviations, as the breakdown point remains equal to 50% (i.e., half of the observations can be replaced by contaminated values) while being more efficient. The main drawback of this measure is its computational complexity.

## Appendix 1.2. Data description

Table 1.3. Descriptive statistics and diagnostic tests based on return series

Indices	N	Annualized returns (%)	Annualized standard deviation (%)	Minimum weekly return (%)	Maximum weekly return (%)	Skewness	Kurtosis	JB test	Unit root and stationarity tests			Ljung-Box tests		
									ADF	PP	KPSS	Returns	Squared returns	
Panel A: Country indices														
Austria	2,345	10.1	17.9	-18.5	14.4	-0.2	5.7	3,236***	-12.5***	-1,963***	0.1	262***	2,197***	
Belgium	2,345	10.7	15.8	-14.4	12.3	-0.5	3.5	1,276***	-14.1***	-1,867***	0.1	195***	1,712***	
Denmark	2,345	12.3	16.8	-18.0	12.4	-0.6	4.6	2,211***	-13.9***	-1,932***	0.1	125***	721***	
Finland	1,588	11.7	23.1	-15.5	12.9	-0.3	2.3	376***	-12.0***	-1,373***	0.1	112***	764***	
France	2,345	12.2	18.1	-14.9	10.6	-0.4	2.6	737***	-14.5***	-1,865***	0.1	164***	652***	
Germany	2,345	10.6	16.5	-14.8	10.7	-0.5	2.8	866***	-14.2***	-1,892***	0.1	116***	859***	
Ireland	2,345	12.5	19.3	-16.3	22.7	-0.2	5.3	2,824***	-13.2***	-1,843***	0.1	213***	629***	
Italy	2,345	9.2	21.1	-15.9	13.1	-0.1	1.9	360***	-15.1***	-1,918***	0.1	199***	675***	
Netherlands	2,345	12.2	15.8	-16.3	10.8	-0.7	4.7	2,370***	-14.5***	-1,929***	0.2	141***	1,514***	
Norway	2,017	12.6	22.0	-17.9	16.4	-0.4	3.1	884***	-12.9***	-1,661***	0.1	119***	1,465***	
Portugal	1,495	5.8	17.7	-17.9	11.1	-0.5	3.0	634***	-11.2***	-1,312***	0.1	91***	388***	
Spain	1,643	10.0	18.9	-17.0	11.5	-0.4	2.4	452***	-13.2***	-1,323***	0.1	95***	484***	
Sweden	1,912	14.2	21.1	-15.1	14.8	-0.3	2.3	470***	-12.5***	-1,755***	0.1	71***	892***	
Switzerland	2,345	11.9	14.3	-14.2	8.8	-0.5	2.9	916***	-14.2***	-1,909***	0.1	129***	420***	
United Kingdom	2,345	11.7	17.4	-17.4	23.8	0.1	7.3	5,237***	-14.4***	-1,984***	0.2	127***	816***	
Panel B: Aggregate industry indices														
Basic Materials	2,345	9.9	16.1	-19.5	11.6	-0.8	6.3	4,128***	-13.6***	-1,850***	0.1	191***	1,950***	
Consumer Goods	2,345	9.9	13.4	-15.4	8.0	-0.6	4.7	2,364***	-14.3***	-1,903***	0.1	145***	186***	
Consumer Services	2,345	9.9	12.8	-14.9	8.7	-0.7	4.9	2,501***	-14.3***	-1,928***	0.1	161***	339***	
Financials	2,345	10.5	15.1	-15.3	12.8	-0.4	5.4	2,897***	-14.1***	-1,959***	0.2	163***	1,677***	
Healthcare	2,345	12.0	11.6	-14.9	8.5	-0.8	6.2	3,960***	-14.8***	-1,869***	0.1	123***	213***	
Industrials	2,345	10.9	14.1	-16.1	8.2	-0.8	5.3	3,003***	-14.5***	-1,863***	0.1	157***	718***	
Oil & Gas	2,345	11.7	15.8	-19.1	11.4	-0.6	5.3	2,947***	-14.5***	-1,766***	0.1	139***	838***	
Technology	2,345	11.9	18.2	-19.7	12.3	-0.5	3.8	1,527***	-14.1***	-1,911***	0.1	132***	740***	
Telecom	2,345	9.8	13.8	-11.0	14.8	0.2	5.0	2,432***	-14.1***	-1,886***	0.2	154***	727***	
Utilities	2,345	10.3	11.7	-14.5	7.5	-0.4	4.9	2,401***	-14.4***	-1,790***	0.3	163***	530***	

Notes: This table presents the descriptive statistics and diagnostic tests applied to the weekly return series of 15 aggregate country indices (Panel A) and ten aggregate sector indices (Panel B). We check whether the series are normally distributed using the Jarque–Bera test. We control the presence of unit root using the Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. We also apply the Ljung–Box Q-tests to the return and squared return series to check whether the series are autoregressive and heteroscedastic. The signs \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively. N is the number of weekly observations.

## Appendix 1.3. Main results

**Table 1.4.** Descriptive statistics and diagnostic tests based on the measures of diversification

Measures		Data granularity	Mean (%)	Minimum (%)	Maximum (%)	ADF test	Ljung-Box test
Equally weighted	IDB Relative	Country	41.2	9.0	79.1	-2.7	1,556***
	IDB Absolute	Sector	64.0	32.9	87.8	-2.2	990***
		Firm	77.4	50.9	93.2	-2.2	818***
	DDB Absolute	Sector	40.6	25.2	64.7	-1.7	1,125***
		Firm	65.4	48.3	84.1	-1.8	1,261***
	Ratio-based IDB	Sector	39.4	7.9	79.9	-3.0	1,500***
		Firm	34.7	3.7	76.7	-2.9	1,333***
	Spread-based IDB	Sector	18.6	1.8	47.0	-2.7	2,041***
Firm		10.8	2.0	28.9	-2.8	1,756***	
Capitalization-weighted	IDB Relative	Country	30.6	6.8	72.4	-2.5	1,477***
	IDB Absolute	Sector	50.8	23.8	80.1	-2.4	863***
		Firm	68.2	41.2	89	-2.3	823***
	DDB Absolute	Sector	27.9	14.8	56.1	-1.9	939***
		Firm	50.1	33.4	69	-2.0	808***
	Ratio-based IDB	Sector	31.8	8.2	72.4	-3.0	1,278***
		Firm	36.6	6.1	74.3	-2.5	1,223***
	Spread-based IDB	Sector	16.9	-0.3	47.4	-2.5	1,777***
Firm		17.4	4.7	35.8	-2.3	1,547***	
Maximum decorrelation	IDB Relative	Country	45.6	10.1	83	-2.6	1,563***
	IDB Absolute	Sector	71.0	42.2	89.2	-2.0	1,016***
		Firm	82.9	60.5	94.9	-2.1	790***
	DDB Absolute	Sector	45.1	29.3	68.1	-1.7	1,182***
		Firm	70.5	54.5	86.8	-1.8	1,259***
	Ratio-based IDB	Sector	47.3	14.9	81.3	-2.6	1,523***
		Firm	41.6	11.3	80.2	-2.9	1,409***
	Spread-based IDB	Sector	19.0	4.3	43.3	-1.8	2,119***
Firm		11.0	3.5	26.2	-2.3	1,908***	
Factor exposures (variance ratio)	Local	Sector	18.0	4.2	45.5	-2.4	2,059***
	Industry (regional)	Sector	3.9	1.6	10.0	-2.7	1,054***
		Regional	Sector	13.1	3.4	29.8	-3.9**
	Industry (global)	Sector	3.9	1.4	11.4	-2.6	845***
		Global	Sector	21.7	2.1	61.7	-2.3

*Notes:* This table presents descriptive statistics and diagnostic tests applied to the measures of international (IDB) and domestic (DDB) diversification benefits (Section 1.4.c), as well as factor loadings. We study the main features of the series using unit root tests (Augmented Dickey–Fuller with drift and trend) and autocorrelation tests (Ljung-Box Q-test). The signs \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively.

**Table 1.5.** Linear and non-linear trend tests

Measure			BV (2005)			PY (2009a)		PSY (2017)	
			Trend (%)	$t_{5\%}$	$t_{10\%}$	Trend (%)	$t$ -stat	Wald-stat	
Panel A: Diversification measures									
Equally weighted	IDB Relative	Country	-1.0**	(-3.1)	(-4.4)	-0.7	(-1.0)	(0.3)	
		Sector	-0.4	(-0.5)	(-0.9)	-0.2	(-0.2)	(0.2)	
	IDB Absolute	Firm	-0.2	(-0.3)	(-0.5)	-0.2	(-0.3)	(0.1)	
		Sector	0.3	(0.0)	(0.1)	0.4	(0.8)	(0.2)	
	DDB Absolute	Firm	0.3	(0.1)	(0.2)	0.4	(0.7)	(0.5)	
		Sector	-1.0**	(-3.1)	(-4.3)	-0.8***	(-4.1)	(0.2)	
	Ratio-based IDB	Firm	-1.0**	(-3.4)	(-4.7)	-1.1***	(-6.2)	(0.0)	
		Sector	-0.8**	(-5.1)	(-6.9)	-0.6***	(-7.0)	(5.3)*	
	Spread-based IDB	Firm	-0.5**	(-11.8)	(-13.1)	-0.4***	(-7.9)	(1.1)	
		Country	-0.9**	(-4.2)	(-5.5)	-0.8***	(-4.3)	(0.0)	
Capitalization- weighted	IDB Relative	Sector	-0.5	(-1.1)	(-1.6)	-0.3*	(-1.8)	(0.2)	
		Firm	-0.4	(-0.8)	(-1.3)	-0.3	(-0.3)	(0.1)	
	DDB Absolute	Sector	0.2	(0.1)	(0.2)	0.3	(0.6)	(0.2)	
		Firm	0.2	(0.2)	(0.4)	0.4	(0.7)	(0.3)	
	Ratio-based IDB	Sector	-0.8**	(-4.0)	(-5.1)	-0.6***	(-3.1)	(0.3)	
		Firm	-0.9**	(-2.5)	(-3.5)	-1.0***	(-4.6)	(0.1)	
	Spread-based IDB	Sector	-0.7**	(-4.8)	(-6.3)	-0.8	(-1.5)	(3.3)	
		Firm	-0.4**	(-4.6)	(-6.0)	-0.6**	(-2.2)	(0.1)	
	Maximum decorrelation	IDB Relative	Country	-1.0**	(-2.7)	(-3.9)	-0.7	(-1.0)	(0.2)
			Sector	-0.3	(-0.2)	(-0.5)	-0.0	(-0.1)	(0.3)
IDB Absolute		Firm	-0.1	(-0.2)	(-0.4)	-0.1	(-0.2)	(0.1)	
		Sector	0.3	(0.0)	(0.1)	0.4	(0.7)	(0.3)	
DDB Absolute		Firm	0.3	(0.1)	(0.2)	0.4	(0.9)	(0.4)	
		Sector	-0.8*	(-1.7)	(-2.7)	-0.5	(-0.8)	(1.3)	
Ratio-based IDB		Firm	-1.0**	(-2.4)	(-3.6)	-1.0***	(-6.4)	(0.1)	
		Sector	-0.7**	(-3.1)	(-4.8)	-0.5**	(-2.2)	(15.0)***	
Spread-based IDB		Firm	-0.4**	(-7.0)	(-9.0)	-0.4***	(-3.6)	(0.3)	
		Country	-0.4**	(-7.0)	(-9.0)	-0.4***	(-3.6)	(0.3)	
Panel B: Sectors' weight within the maximum decorrelation portfolio ( $\times 10$ )									
Sectors' weight	Basic Materials		0.8**	(5.6)	(6.2)	0.8***	(3.7)	(3.3)	
	Consumer Goods		-0.4	(-0.8)	(-1.0)	0.0	(0.0)	(0.1)	
	Consumer Services		-0.0	(-0.2)	(-0.3)	0.8	(0.9)	(0.6)	
	Financials		-0.4	(-0.8)	(-1.1)	-0.4	(-1.5)	(0.3)	
	Healthcare		1.6	(0.9)	(1.7)	-0.4	(-0.2)	(8.7)**	
	Industrials		-1.2**	(-9.8)	(-10.7)	-1.2***	(-7.9)	(0.7)	
	Oil & Gas		-0.4	(-0.2)	(-0.3)	-0.4	(-0.1)	(0.1)	
	Technology		-1.6*	(-1.3)	(-2.0)	-0.8	(-0.4)	(0.4)	
	Telecom		0.8	(0.8)	(1.2)	0.4	(0.3)	(0.0)	
	Utilities		0.0	(0.2)	(0.2)	0.8	(0.4)	(0.0)	
Panel C: Factor analysis									
Factor Exposures (variance ratio)	Local		-0.8**	(-4.0)	(-6.0)	-0.7	(-1.4)	0.5	
	Industry (regional)		0.1**	(2.1)	(2.9)	0.1***	(5.0)	0.0	
	Regional		0.0	(0.4)	(0.5)	-0.0	(-0.2)	1.2	
	Industry (global)		0.1	(0.5)	(1.0)	0.1	(0.4)	0.0	
	Global		0.7	(0.6)	(1.2)	0.4	(0.5)	0.3	

*Notes:* This table presents the results of three deterministic trend tests, which are valid whether the errors are I(0) or I(1). We report the annualized trends (%) and t-statistics (in parentheses) based on the linear trend test of [Bunzell and Vogel-sang, 2005](#) (BV). The null hypothesis is that there is no trend in the series. The 5% and 10% critical values (two-sided) are 2.1 and 1.7, respectively. We also use the test of [Perron and Yabu, 2009a](#) (PY), for comparison purposes. The 10%, 5%, and 1% critical values are 1.6, 2.0, and 2.6, respectively. Finally, we check for the presence of non-linear deterministic trends based on [Perron et al., 2017](#) (PSY). The null hypothesis is that the non-linear components are not different than zero. The critical values for the Wald statistic are 4.6, 6.0, and 9.2 at 10% (\*), 5% (\*\*), and 1% (\*\*\*) significance levels, respectively. *Abbreviations:* International diversification benefits (IDB); Domestic diversification benefits (DDB).

**Table 1.6.** Comparison with other studies

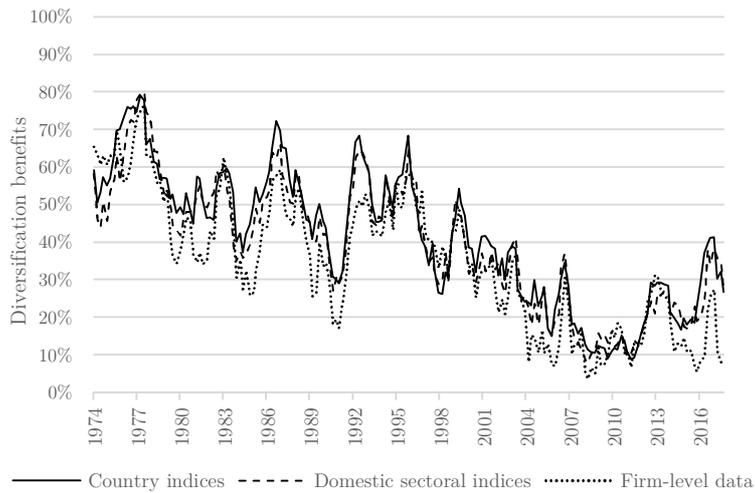
Papers	Time frame	Comparative base	Standard IDB measure			Ratio-based IDB measure		
			Country	Sector	Firm	Country	Sector	Firm
King et al. (1994)	1973–1988	16 advanced countries	-0.7 (-0.0)	-0.4 (-0.0)	-0.6 (-0.1)	-0.7 (-0.0)	-0.8 (-0.0)	-1.6 (-0.2)
Kaltenhäuser (2002)	1988–2002	Europe & the US	-0.9 (-0.9)	0.5 (0.6)	0.7 (0.6)	-0.9 (-0.9)	-0.9 (-0.8)	-0.3 (-0.1)
Berben and Jansen (2005)	1980–2000	4 advanced countries	-0.4 (-0.6)	0.4 (1.1)	0.8** (3.0)	-0.4 (-0.6)	-0.3 (-0.5)	0.1 (0.2)
Kearney and Poti (2006)	1993–2002	5 European countries	-2.4 (-0.1)	-0.4 (-0.0)	0.0 (0.0)	-2.4 (-0.1)	-2.6 (-0.4)	-1.9 (-0.2)
Pukthuanthong and Roll (2009)	1973–2008	82 countries	-1.0** (-5.8)	-0.2 (-1.1)	0.1 (0.3)	-1.0** (-5.8)	-0.9** (-5.2)	-1.0** (-3.4)
Bekaert et al. (2009)	1980–2005	23 countries	-0.8** (-2.9)	0.1 (0.5)	0.5* (2.5)	-0.8** (-2.9)	-0.7** (-2.8)	-0.5 (-1.3)
Christoffersen et al. (2014)	1973–2012	16 advanced countries	-1.2** (-5.1)	-0.6 (-0.8)	-0.3 (-0.2)	-1.2** (-5.1)	-1.2** (-5.0)	-1.2** (-3.8)
Evans et al. (2017)	2000–2013	G7 countries	-2.3 (-0.8)	-2.7 (-0.7)	-1.9 (-0.6)	-2.3 (-0.8)	-2.0* (-2.3)	-1.7 (-0.5)
Billio et al. (2017)	1973–2016	16 advanced countries	-1.2** (-5.7)	-0.6 (-1.1)	-0.2 (-0.3)	-1.2** (-5.7)	-1.1** (-5.4)	-1.1** (-4.0)

*Notes:* This table performs trend tests (Bunzell and Vogelsang, 2005) on the standard and ratio-based IDB series (obtained from our sample of European markets) over the periods used in the selected papers. These studies focus on the correlation between European stock markets (among other countries). Trends are expressed in percentage point increase or decrease per year. We report the adjusted t-statistics for the 10% critical value (two-sided test) in parentheses. We do not present the t-statistic for the 5% critical value but take it into account in the significance level. The signs \* and \*\* indicate significance at the 10% and 5% level, respectively.

**Table 1.7.** Structural breaks in trends

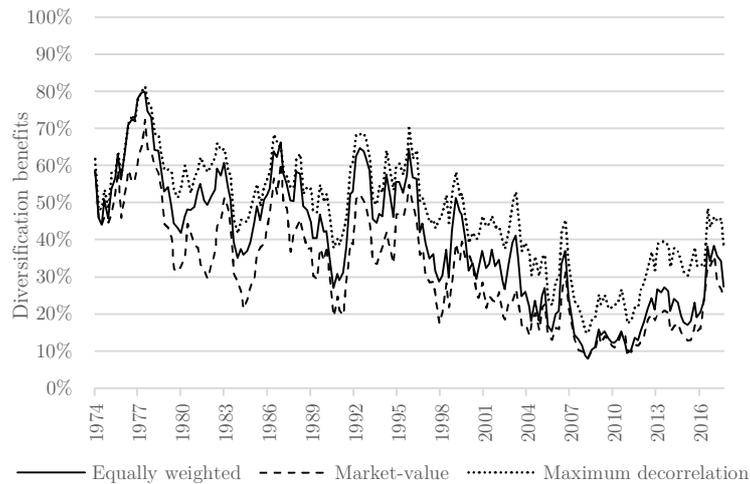
Measure	Portfolio	Data granularity	Break date	$W_{RQF}$	First sub-period		Second sub-period	
					Trend (%)	$t_{10\%}$	Trend (%)	$t_{10\%}$
Ratio-based IDB	Equally weighted	Country	2008:04	(1.0)	-1.0**	(-5.9)	2.0	(0.0)
		Sector	2008:04	(0.9)	-1.0**	(-5.2)	2.0	(0.0)
		Firm	1992:11	(0.6)	-1.7*	(-1.8)	-1.6*	(-2.3)
	Capitalization weighted	Country	2008:10	(0.7)	-1.1**	(-6.9)	1.6	(0.0)
		Sector	2008:07	(0.8)	-0.9**	(-5.4)	1.6	(0.0)
		Firm	1992:11	(0.7)	-1.4*	(-1.9)	-1.6**	(-3.9)
	Maximum decorrelation	Country	2008:04	(1.3)	-1.0**	(-5.8)	2.4	(0.0)
		Sector	2008:04	(0.8)	-0.8**	(-4.3)	2.4	(0.5)
		Firm	1992:11	(0.8)	-1.7	(-1.1)	-1.4	(-1.6)
Spread-based IDB	Equally weighted	Sector	1997:09	(1.0)	-0.8**	(-3.5)	-0.2	(-1.5)
		Firm	2001:08***	(4.8)	-0.5**	(-6.8)	-0.1*	(-1.8)
	Capitalization weighted	Sector	1998:03	(0.8)	-0.8**	(-3.9)	0.1	(1.2)
		Firm	2002:02	(1.4)	-0.2	(-1.5)	-0.2	(-0.9)
	Maximum decorrelation	Sector	1996:08***	(6.2)	-0.7**	(-3.9)	-0.1	(-0.6)
		Firm	2000:04***	(6.2)	-0.5**	(-6.8)	-0.1	(-0.9)

*Notes:* This table checks for structural breaks in the intercept and slope of the linear trend test applied to (i) the *ratio-based* IDB indicator and (ii) the *spread-based* IDB measure. We use the test developed by Perron and Yabu (2009b) and report the break dates and the test statistics ( $W_{RQF}$ ). The critical values for  $W_{RQF}$  are 2.7, 3.2, and 4.6 at 10% (\*), 5% (\*\*), and 1% (\*\*\*) significance levels, respectively. We then recompute Bunzell and Vogelsang's (2005) trend tests over the corresponding sub-periods. The adjusted t-statistics for the 10% critical value (two-sided test) are reported in parentheses. We do not present the t-statistic for the 5% critical value but take it into account in the degree of significance.



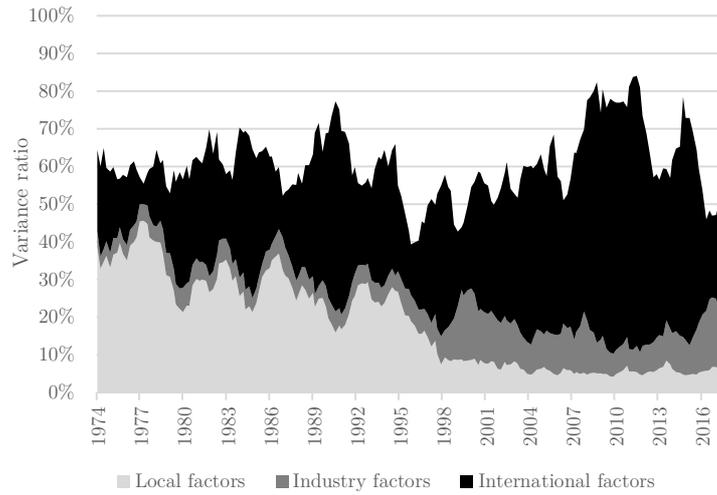
**Figure 1.5. European diversification benefits using the ratio-based IDB measure**

This figure examines the dynamics of the relative benefits of European diversification using the ratio-based measure. We use (i) country indices (solid line), (ii) domestic sectoral indices (dashed line), and (iii) firm-level data (dotted line). These results are based on equally weighted portfolios and estimated using one-year rolling windows.



**Figure 1.6. European diversification benefits based on various portfolio-weighting schemes**

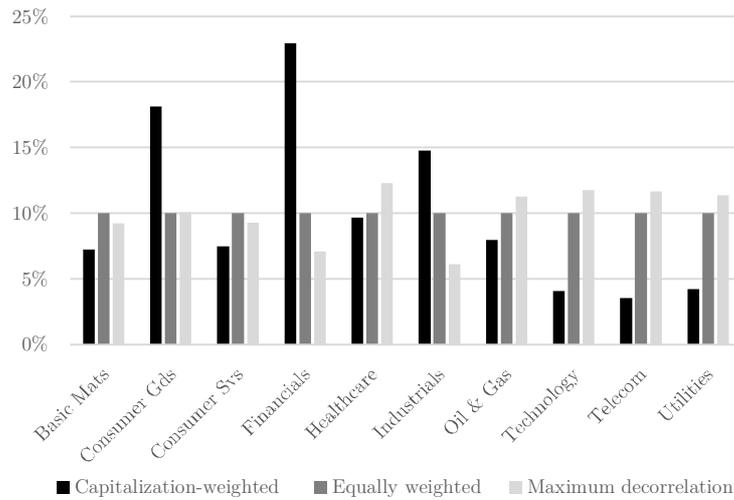
This figure depicts the evolution of the relative benefits of European diversification based on equally weighted (solid line), capitalization-weighted (dashed line), and maximum decorrelation (dotted line) portfolios. The results presented here are based on the adjusted IDB measure, using domestic sectoral portfolios.



**Figure 1.7. Factor influence based on a variance ratio**

This figure represents the percentage of the variance of the average domestic portfolio explained by the variance of a set of country (light grey area), industry (regional & global; dark grey area), and international factors (regional & global; black area). The results illustrated here are based on an equally weighted average using one-year rolling window estimates.

## Appendix 1.4. European equity portfolios—additional insights



**Figure 1.8. Sectors' weights within European portfolios**

This figure depicts the importance of each sector as a percentage of the market capitalization of the European portfolios. We present the results for capitalization-weighted (black bar), equally weighted (dark grey bar), and maximum decorrelation (light grey bar) portfolios, as of 2018 (last observation observable).

**Table 1.8. Domestic holdings in the equity portfolios (by country, in %)**

	AT	BE	DK	FI	FR	DE	IT	NL	NO	PT	ES	SE	CH	GB
Domestic holdings, 2001	36	48	58	79	79	62	64	53	55	84	82	60	65	74
Domestic holdings, 2017	36	36	44	35	58	48	31	30	18	50	58	43	51	36

*Source:* IMF (Coordinated Portfolio Investment Survey).

*Notes:* We analyze the shares of domestic holdings in the equity portfolios of investors domiciled in each country of our sample. 2001 and 2017 are the first and last available annual observations, respectively.

*Abbreviations:* Austria (AT); Belgium (BE); Denmark (DK); Finland (FI); France (FR); Germany (DE); Italy (IT); Netherlands (NL); Norway (NO); Portugal (PT); Spain (ES); Sweden (SE); Switzerland (CH); United Kingdom (GB).

## Appendix 1.5. Robustness tests

Table 1.9. Excluding countries

Panel A: Eurozone vs. Non-eurozone members															
Measure		Euro area countries (n=11)			Non-euro area countries (n=4)										
		Trend (%)	$t_{5\%}$	$t_{10\%}$	Trend (%)	$t_{5\%}$	$t_{10\%}$								
IDB Relative	Country	-1.2**	(-3.0)	(-4.3)	-1.4**	(-6.0)	(-7.3)								
	Sector	-0.4	(-0.3)	(-0.6)	-0.4	(-0.2)	(-0.5)								
IDB Absolute	Firm	-0.2	(-0.1)	(-0.2)	n/a	n/a	n/a								
	Sector	0.3	(0.1)	(0.2)	0.2	(0.0)	(0.1)								
DDB Absolute	Firm	0.3	(0.0)	(0.1)	n/a	n/a	n/a								
	Sector	-0.9*	(-1.9)	(-2.9)	-0.7**	(-3.5)	(-4.4)								
Ratio-based IDB	Firm	-1.1**	(-3.1)	(-4.4)	n/a	n/a	n/a								
	Sector	-0.7**	(-4.8)	(-6.5)	-0.5**	(-5.6)	(-6.9)								
Spread-based IDB	Firm	-0.4**	(-7.0)	(-8.9)	n/a	n/a	n/a								

Panel B: Relative IDB (country-based)—Robustness to the exclusion of one country															
Excl. Country	AT	BE	DK	FI	FR	DE	IE	IT	NL	NO	PT	ES	SE	CH	GB
Trend (%)	-0.9**	-0.9**	-0.9**	-0.9**	-0.8**	-0.8**	-0.9**	-0.9**	-0.9**	-1.0**	-0.9**	-0.9**	-0.9**	-0.9**	-0.8**
$t_{5\%}$	(-3.8)	(-4.4)	(-4.4)	(-4.2)	(-4.1)	(-3.3)	(-4.5)	(-4.2)	(-4.5)	(-4.4)	(-4.2)	(-4.3)	(-4.1)	(-4.9)	(-3.6)
$t_{10\%}$	(-5.1)	(-5.7)	(-5.6)	(-5.4)	(-5.3)	(-4.4)	(-5.8)	(-5.5)	(-5.7)	(-5.7)	(-5.4)	(-5.7)	(-5.3)	(-6.1)	(-4.6)

*Notes:* This table presents the results of the trend test of [Bunzell and Vogelsang \(2005\)](#) applied to the IDB measures. Panel A compares the evolution of IDB within (i) euro area countries and (ii) non-euro area countries. These measures are based on equally weighted portfolios. Panel B presents the relative IDB (using country indices) based on capitalization-weighted portfolios. For each series, we exclude one country from the computation of the IDB measure. The signs \* and \*\* indicate significance at the 10% and 5% level, respectively. *Abbreviations:* Austria (AT); Belgium (BE); Denmark (DK); Finland (FI); France (FR); Germany (DE); Ireland (IE); Italy (IT); Netherlands (NL); Norway (NO); Portugal (PT); Spain (ES); Sweden (SE); Switzerland (CH); United Kingdom (GB).

**Table 1.10.** Alternative specifications

	IDB measure	BV (2005)		
		Trend (%)	$t_{5\%}$	$t_{10\%}$
Ratio-based IDB (Sector)	Standard	-1.0**	(-3.1)	(-4.3)
	Two-year rolling window	-1.0*	(-2.0)	(-3.3)
	Monthly returns	-1.2**	(-5.7)	(-6.6)
	Spearman correlation	-1.0**	(-2.7)	(-4.0)
	Without diagonal	-1.4**	(-5.0)	(-6.6)
Spread-based IDB (Sector)	Standard	-0.8**	(-5.1)	(-6.9)
	Two-year rolling window	-0.8*	(-3.6)	(-5.7)
	Monthly returns	-0.8**	(-5.2)	(-6.7)
	Spearman correlation	-0.7**	(-4.7)	(-6.6)
	With diagonal	-0.7**	(-5.1)	(-6.9)

*Notes:* This table presents the results of the trend test of [Bunzell and Vogelsang, 2005](#) (BV) applied to the ratio- and spread-based measures for alternative specifications of the estimation method. All the series are based on local industries and equally weighted portfolios. We control that the results are robust to (i) various sizes of rolling window (two- vs. one-year), (ii) different data frequencies (monthly vs. weekly returns), (iii) alternative correlation estimators (Spearman vs.  $Q_n$  estimator), and (iv) the exclusion (or inclusion) of the diagonal of the correlation matrix in the computation of the average comovements.

## Chapter 2

# The Long-Term Effect of Globalization on International Stock Return Comovements

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This chapter was presented at the CERECE Conference on Financial and Economic Integration (Brussels, 2019).

## 2.1. Introduction

The comovements among international stock returns—or stock market interdependencies<sup>7</sup>—have significantly increased over the past four decades. This rise is an issue for investors, as it limits the benefits of international portfolio diversification. Regulators are also concerned insofar as it could undermine the stability of the financial system by facilitating the propagation of shocks between countries. To address these issues, investors and regulators need a better understanding of the determinants of the rise in stock market comovements.

While a large body of literature provides evidence of increased interdependencies among equity markets (see Chapter 1 for a review), less effort was devoted to uncovering the mechanisms behind this process on the empirical side. Papers have mainly investigated the determinants of the short-term changes in stock market comovements, with conflicting results. They disagree on the specific impact of trade and financial linkages on equity market interdependencies. By contrast, almost no studies explore the determinants of the long-term evolution in stock market comovements. Yet, this approach is better suited to identifying the mechanisms underlying the four-decade-rise in equity market interdependencies, considering that some of the short-term changes in comovements tend to reverse themselves (e.g., Hunter, 2005; Quinn and Voth, 2008). One explanation for this research gap was the lack of models to estimate long-term relationships in macro panel datasets. This chapter contributes to filling this gap by studying the determinants of the rise in stock market comovements based on the dynamic panel models introduced by Chudik and Pesaran (2015) and Chudik et al. (2016).

We test the main hypotheses proposed in the theoretical literature to explain the interdependencies among equity markets (see Dornbusch et al., 2000). Overall, the degrees of trade and financial openness are assumed to be drivers of stock market interdependencies. Open economies are exposed to common trade and financial shocks, which in turn can lead to synchronous adjustments in national stock markets. In addition, trade or financial linkages enable shocks to propagate between countries, which could determine the degree of interdependencies among stock markets. The literature also pays attention to a specific type of financial open-

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<sup>7</sup> The terms interdependencies and comovements describe the relationship between two variables, in both normal and crisis times, and assume no causal link between them.

ness—the openness of equity markets to international investors<sup>8</sup>—that can influence stock market interdependencies through three channels. First, equity market openness can convey financial shocks that impact the cost of capital across open economies. Second, foreign shareholders can improve the informational efficiency of local stock markets (Bae et al., 2012), reinforcing the impact of trade and financial ties on stock market comovements. Third, global investors are likely to transmit shocks across equity markets, even in the absence of fundamental links between countries. For example, following an adverse shock in a domestic equity market, investors with risk or liquidity constraints may be forced to sell their positions in other equity markets, leading to a synchronized decline in international stock prices. We refer to the latter channel as the “non-fundamental investor-based linkages.”

Based on these hypotheses, this chapter examines whether the rise in stock market comovements over the past four decades stems from increased trade or financial openness. Our empirical analysis is based on a sample of 47 developed and developing markets<sup>9</sup>—following the MSCI typology—from 1973 to 2018. We build annual comovement measures based on weekly return series. We use both *de jure* and *de facto* explanatory factors. Trade openness indicators are based on (i) the volume of trade flows relative to GDP and (ii) the state of trade openness policies. We measure broad financial openness based on (i) cross-border capital holdings and (ii) the state of capital openness policies. Finally, we capture equity market openness using cross-border equity holdings.

Our results enrich the previous literature in several ways. We find evidence that the mechanisms behind the rise in stock market interdependencies are different in advanced and emerging market economies. Specifically, we show that the surge in comovements among developed markets is due to increased trade linkages. By contrast, growing interdependencies (i) among emerging markets and (ii) between developing and developed markets stem from increased foreign holdings of emerging stocks. This result contributes to the debate on the pros and cons of equity market liberalization (see [Section 2.7](#)).

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<sup>8</sup> International investors represent a range of shareholders, such as hedge funds, mutual funds, pension funds, sovereign wealth funds, insurers, banks, and some individual investors.

<sup>9</sup> We make no distinction between the terms (i) “advanced” and “developed” and (ii) “emerging” and “developing”.

Our findings also shed new light on the role of international shareholders on equity market comovements. We complement previous studies by showing that there are a cointegration and a long-term relationship between foreign equity investments and the rise in emerging market interdependencies. Furthermore, estimating comovements among national stock markets leads to a *relative* measure of international diversification benefits, which compares the gain of holding a global portfolio instead of the average domestic one (see Chapter 1). Therefore, our approach based on market-level data allows us to examine whether foreign shareholders drive the long-term decline in international diversification benefits.

Our analysis reveals the existence of an international diversification puzzle. In theory, investors should invest in the equity markets that exhibit the lowest degree of comovements with the rest of the world to maximize diversification benefits. However, our results support the idea that the very search for investment opportunities in emerging markets causes an increase in emerging market comovements, which in turn leads to a decline in the relative IDB. Moreover, our results suggest that non-fundamental investor-based linkages could be at the root of the rise in emerging market comovements. This fact is a potential risk to financial stability, which might call for international regulation of equity flows.

The remainder of this chapter is organized as follows: Section 2.2 provides a review of the related literature; Section 2.3 explains the methodology; Section 2.4 describes the data; Section 2.5 presents the results; Section 2.6 reports the robustness tests; Section 2.7 discusses the contributions of the chapter; Section 2.8 concludes.

## 2.2. Related literature

A growing body of literature underscores the importance of trade and financial linkages as a potential driver of stock market interdependencies. Wälti (2011) documents that trade and financial ties are significant determinants of the comovements among advanced markets. Beine and Candelon (2011) find similar conclusions for emerging markets. The IMF (2016) also reveals that both trade and financial linkages affect shock propagation among developing markets and from emerging markets to developed markets. However, previous papers tend to disagree on the relative importance of trade and financial ties to explain the increase in equity market

interdependencies. Mixed results may be due to heterogeneous samples, different econometric approaches, and various indicators of trade and financial openness.

On the one hand, [Forbes and Chinn \(2004\)](#) argue that direct trade links are the main determinants of market comovements, while the impact of capital flows is insignificant. [Bekaert et al. \(2016\)](#) findings are less clear-cut but still suggest that trade globalization is more relevant than financial globalization to explain stock market interdependencies, especially for advanced market economies. [Beine et al. \(2010\)](#) examine the determinants of stock market coexceedances. They note that financial openness only increases left tail comovements, while trade openness impacts comovements across all quantiles. [Paramati et al. \(2018\)](#) highlight that bilateral trade linkages have a long-term effect on the relationship between the Chinese and the Australian stock markets. [Barrot et al. \(2019\)](#) note that stock prices of US companies reflect the exposure to international trade, leading to increased comovements between exporting firms.

On the other hand, [Quinn and Voth \(2008\)](#) find that financial openness has been the main driver of advanced market comovements over the last century. [Baele and Soriano \(2010\)](#) document that rising exposures of European stock markets to US shocks are mainly due to an increase in the discount rate beta, highlighting the dominant role played by financial integration on the rise in stock market comovements. [Eiling and Gerard \(2015\)](#) show that capital liberalization in emerging countries is the main explanatory factor of rising stock market interdependencies. [Chuluun \(2017\)](#) reports that all types of capital links, including equity flows, have a positive effect on bilateral stock market correlations. [Ando \(2019\)](#) reaches similar conclusions in his paper. Finally, [Anagnostopoulos et al. \(2019\)](#) note that foreign direct investments have a positive long-term effect on the degree of stock market interdependencies.

This chapter is also related to studies analyzing the impact of international shareholders on stock market comovements. Some papers focus on the degree of accessibility of stocks in developing markets. [Boyer et al. \(2006\)](#) reveal that emerging stocks that are eligible for purchase by non-residents exhibit larger comovements during crisis episodes. [Bae et al. \(2012\)](#) note that a higher degree of market accessibility facilitates the dissemination of global market information among investible stocks. Other articles study the impact of foreign institutional holdings on stock market comovements. [Bartram et al. \(2015\)](#) show that common ownership can explain international stock return comovements beyond the traditional country, industry, and global

factors. [Faias and Ferreira \(2017\)](#) find that institutional ownership increases the relative importance of industry and global factors compared to country factors, implying larger stock market comovements.

Other papers examine the existence of non-fundamental investor-based linkages using data on the inclusion of companies in major stock market indices. For instance, [Claessens and Yafeh \(2013\)](#) report that, in most countries, firms experienced an increase in their local betas after their inclusion in the national stock market index. The literature has also explored the influence of investment managers on equity market interdependencies based on mutual fund data. [Jotikasthira et al. \(2012\)](#) emphasize that funds can face allocation constraints due to funding shocks from their investor base. These constraints lead them to transmit significant financial shocks between stock markets, particularly in emerging countries. [Raddatz et al. \(2017\)](#) analyze the impact of benchmark indices on asset allocation and asset prices. Based on several case studies, they stress that changes in benchmarks drive coordinate response from asset managers, leading to non-fundamental comovements among stock markets. Finally, focusing on the Chinese stock market, [Li et al. \(2019\)](#) examine the impact of the trading behavior of different types of investors (individual investors, funds, foreign institutional investors, insurance, and state-owned companies) on the comovements among Chinese stocks. They show that only fund flows positively and significantly affect stock return comovements.

The main contributions of this chapter are the following:

- First, we study the determinants of the long-term evolution in stock market interdependencies. This approach is better suited to identifying the mechanisms behind the rise in equity market comovements, considering that some of the short-term dynamics in comovements tend to reverse themselves.
- The second contribution is related to the econometric tool. We use dynamic models that are appropriate to study long-term relationships in macro panel datasets. By contrast, standard panel models do not handle non-stationary series, omitted factors, and feedback effects, which can lead to inconsistent estimates and spurious regressions. To the best of our knowledge, only [Anagnostopoulos et al. \(2019\)](#) explore the determinants of the long-term evolution of stock market comovements using a CS-ARDL model.

However, they focus on the effect of foreign direct investments based on a restricted sample (six advanced markets).

- Third, we decompose financial links between cross-border capital holdings (excluding equities) and cross-border equity holdings to specifically assess the role of foreign shareholders on stock market comovements. Since emerging markets are usually considered as a separate asset class by investors (Bekaert and Harvey, 2014), we also control for differences between the determinants of the comovements (i) among advanced markets, (ii) among emerging markets, and (iii) between developing and developed markets.
- Finally, our results enrich the literature with macro evidence of the long-term effect of foreign investors on equity market interdependencies and underline the existence of an international diversification puzzle.

### 2.3. Methodology

Standard panel estimators are not robust to non-stationary variables, slope heterogeneity, and cross-sectional dependence, which are common features in macroeconomic and financial series. In this section, we describe the dynamic panel models of Chudik and Pesaran (2015) and Chudik et al. (2016) that deal with the specificities of macro panel data (i.e., relatively large cross-sectional and time dimensions).

Chudik and Pesaran (2015) rely on the estimation of unit-specific autoregressive distributed lag (ARDL) models, appropriately augmented with the cross-sectional averages (CSA) of the dependent and independent variables to filter out the effects of unobserved common factors. The long-term effects are indirectly drawn from the estimates of the short-term parameters. Chudik and Pesaran (2015) refer to this approach as the cross-sectionally augmented ARDL (or CS-ARDL in short):

$$y_{i,t} = \alpha_i + \sum_{l=1}^{p_y} \lambda_{i,l} y_{i,t-l} + \sum_{l=0}^{p_x} \beta_{i,l} x_{i,t-l} + \sum_{l=0}^{p_T} \gamma_{i,l} \bar{z}_{t-l} + e_{i,t} \quad (2.1)$$

where  $\bar{z}_t = (\bar{y}_{t-1}, \bar{x}_t)$  are the CSA of the dependent and independent variables.  $p_y$  and  $p_x$  are the number of lags of the dependent and independent variables.  $p_T$  represents the number of lags of the CSA, which should be approximately equal to  $\sqrt[3]{T}$ , with T the time dimension of

the panel dataset. A disadvantage of the ARDL model is that the number of lags of the dependent and independent variables  $p_y$  and  $p_x$  needs to be known. Underestimating the lag order produces inconsistent estimates while overestimating it could result in a loss of efficiency. The sampling uncertainty can also be large when the speed of convergence toward the long-term relationship is slow and the time dimension is not large enough.

Chudik et al. (2016) also develop the cross-sectionally augmented distributed lag (CS-DL) model—based on a distributed lag representation that does not include lags of the dependent variable—to estimate long-term effects in dynamic heterogeneous panels with cross-sectionally dependent errors. While the CS-ARDL model uses an auxiliary regression to determine the long-term coefficients  $\theta_i$ , the CS-DL model can estimate them directly as follows:

$$y_{i,t} = \theta_{0,i} + \theta_{1,i}x_{i,t} + \sum_{l=0}^{p_x-1} \delta_{i,l}\Delta x_{i,t-l} + \gamma_{y,i}\bar{y}_{i,t} + \sum_{l=0}^{p_T} \gamma_{x,i,l}\bar{x}_{i,t-l} + e_{i,t} \quad (2.2)$$

The CS-DL approach has a better small sample performance than the CS-ARDL model for moderately large time dimensions ( $30 < T < 100$ ). However, the CS-DL approach is complementary but not superior to the CS-ARDL model. Unlike the CS-ARDL approach, the CS-DL method does not consider the feedback effects of the explained variable on the explanatory factors. Still, it allows for residual factor error structure and weak cross-sectional dependence in the errors. Following Chudik et al. (2016), we use both the CS-ARDL and CS-DL models to estimate the long-term effect of trade and financial links on stock market comovements. Both approaches can handle I(0) and I(1) variables.

When the time dimension is large enough, Pesaran and Smith (1995) show that the coefficients can be estimated using ordinary least squares by (i) running separate time-series regression for each group and (ii) calculating the unweighted average of the cross-section of individual coefficients (mean group—MG—estimator). This approach is consistent whether the coefficients are homogeneous or heterogeneous across countries. This characteristic is particularly important in the case of dynamic models since incorrectly ignoring coefficient heterogeneity induces serial correlation in the residuals, leading to inconsistent estimates. The main drawback of the MG estimator is that it is sensitive to potential outliers in individual coefficients.

## 2.4. Data

This section details the sample and describes our measures of stock market comovements based on factor models and correlation estimators. Then, we review the main indicators of trade and financial openness proposed in the literature and discuss our selection.

### *2.4.a. Sample*

Our empirical analysis is based on 47 domestic stock markets, including 24 advanced and 23 emerging and frontier markets, over the period 1973–2018 (see Table 2.1). In the rest of the chapter, we do not distinguish between emerging and frontier markets due to the lack of data on frontier market economies. Since the introduction of the MSCI classification in 1988, only Portugal (1997), Greece (2001, 2013), and Israel (2010), have moved from the emerging category to the advanced one. We use Datastream indices instead of the indices provided by local stock exchanges, as (i) they are built according to a unique methodology and (ii) they cover a large number of markets over extended time frames. There is no overlap between indices, as foreign listings are excluded from each index. The time dimension must be large enough for the parameters to be accurately estimated. Therefore, we only select national indices available over more than 20 years. Our sample covers some of the largest developing stock markets, such as Brazil, China (H+B shares), and India. However, we cannot include Russia or Indonesia in our sample, as Datastream indices are not available before 1998 for these countries.

We deal with missing data, the non-alignment of time zones, and the differences of currencies following the approach detailed in Chapter 1 (see Section 1.4.a). We calculate weekly returns using total return indices denominated both in US dollars and in local currency to control for the impact of currency risk on comovement measures.

**Table 2.1.** Description of the data

Country	ISO code	GNI per capita	Classification	Starting date
Switzerland	CH	83,580	Advanced	1973
Norway	NO	80,790	Advanced	1980
Luxembourg	LU	77,820	Advanced	1992
United States	US	62,850	Advanced	1973
Denmark	DK	60,140	Advanced	1973
Ireland	IE	59,360	Advanced	1973
Singapore	SG	58,770	Advanced	1973
Sweden	SE	55,070	Advanced	1982
Australia	AU	53,190	Advanced	1973
Netherlands	NL	51,280	Advanced	1973
Hong Kong	HK	50,310	Advanced	1973
Austria	AT	49,250	Advanced	1973
Finland	FI	47,820	Advanced	1988
Germany	DE	47,450	Advanced	1973
Belgium	BE	45,430	Advanced	1973
Canada	CA	44,860	Advanced	1973
Japan	JP	41,340	Advanced	1973
United Kingdom	GB	41,330	Advanced	1973
France	FR	41,070	Advanced	1973
Israel	IL	40,850	Advanced	1993
New Zealand	NZ	40,820	Advanced	1988
Italy	IT	33,560	Advanced	1973
Korea	KR	30,600	Emerging	1987
Spain	ES	29,450	Advanced	1987
Cyprus	CY	26,300	Emerging	1993
Portugal	PT	21,680	Advanced	1990
Czech Republic	CZ	20,250	Emerging	1993
Greece	GR	19,540	Emerging	1990
Chile	CL	14,670	Emerging	1989
Hungary	HU	14,590	Emerging	1991
Poland	PL	14,150	Emerging	1994
Argentina	AR	12,370	Emerging	1993
Malaysia	MY	10,460	Emerging	1986
Turkey	TR	10,380	Emerging	1988
China	CN	9,470	Emerging	1995
Mexico	MX	9,180	Emerging	1989
Brazil	BR	9,140	Emerging	1994
Thailand	TH	6,610	Emerging	1987
Peru	PE	6,530	Emerging	1994
Colombia	CO	6,190	Emerging	1992
South Africa	ZA	5,720	Emerging	1973
Sri Lanka	LK	4,060	Frontier	1987
Philippines	PH	3,830	Emerging	1987
Morocco	MA	3,090	Frontier	1994
India	IN	2,020	Emerging	1990
Pakistan	PK	1,580	Emerging	1992
Venezuela	VE	n/a	Frontier	1994

*Notes:* The table ranks the countries in ascending order according to their gross national income (GNI) per capita (as of 2018) in dollars. We report whether stock markets are advanced, emerging, or frontier according to the MSCI classification. Luxembourg, Cyprus, and Venezuela are not included in the MSCI indices. We classify Luxembourg as an advanced market and Cyprus and Venezuela as emerging and frontier markets, respectively. The MSCI classification framework is based on economic development, size and liquidity requirements, and market accessibility criteria.

### 2.4.b. Comovement measures

The literature has proposed several measures to capture the dynamics of stock market comovements. Our baseline indicator, named *PCA*, is a factor-based approach introduced by Pukthuanthong and Roll (2009). The measure represents the percentage of the variance of each domestic equity index explained by a set of international factors. These factors are derived from the data using a principal component analysis based on standardized variables. For each available calendar year, we estimate and sort eigenvectors from the largest to the smallest. Following Pukthuanthong and Roll, we use the first ten principal components as international factors, which serve as explanatory variables to the returns of each country index:

$$R_{i,t} = \alpha_i + \sum_{j=1}^N \beta_{i,j} F_{j,t} + \varepsilon_{i,t}$$

where  $R_i$ , a  $(T \times 1)$  vector, represents the returns of the country index  $i$ .  $T$  is the number of observations.  $F_j$  is a  $(T \times 10)$  matrix containing the ten first principal components.  $\beta_{i,j}$  are the factor loadings and  $\varepsilon_i$  represents the model errors. Factors and residuals are uncorrelated. We use the adjusted R-squared of these regressions as a measure of stock market comovements. Pukthuanthong and Roll recommend estimating the global factors from the country indices available over the entire time frame (1973–2018). Otherwise, the nature of the global factors may change over time, as data for more country indices become available, leading to potential structural breaks in the comovement measures. As a precaution, for each of the 17 initial markets, separate principal components are estimated based on the 16 other initial markets. In our dataset, these 17 markets also happen to be among the most advanced and open markets in the world. Hence, our baseline indicator captures the degree of comovements between each domestic market and the world's major equity markets. Pukthuanthong and Roll (2009) perform an out-of-sample analysis to alleviate the possibility that sampling errors bias the principal components. They use the eigenvectors from one period as weights for returns in the next period. However, based on this approach, we lose the first annual observation and the information contained in the last year of the sample. Moreover, their method is not robust to potential structural break in the weights during crisis episodes. Therefore, we prefer to rely on standard (in-sample) principal component analysis.

Using this baseline approach, we design several alternative measures that vary with the underlying data and factors selected. Our primary indicator, *PCA*, is based on 47 domestic equity indices denominated in US dollars. Alternatively, we construct a measure based on indices denominated in local currencies, which does not account for the impact of currency risk on shock transmission (*PCA-local-currency*). We also build an indicator of comovements based on domestic sectoral portfolios instead of country indices (*PCA-local-sector*). Finally, we develop a measure of interdependencies using global factors that are derived from the entire dataset rather than the 17 initial markets (*PCA-all-markets*).

We also build related measures based on observable factor models. Specifically, we use the world equity index from Datastream as a global factor instead of the first ten principal components. The first indicator represents the percentage of the variance of the domestic equity indices explained by the world equity index (*ICAPM-R<sup>2</sup>*). The other one is the exposure of each country index to the world market factor (*ICAPM-beta*). Finally, we construct a measure based on the average pair-wise correlation between each domestic market and the 17 initial markets (*Correlation*), such as:

$$Correlation_{i,t} = \frac{\sum_{j=1}^N \rho_{i,j,t}}{N}$$

in which  $\rho_{i,j,t}$  stands for the Spearman correlation coefficient between the domestic markets  $i$  and  $j$  at date  $t$ .  $N$  represents the number of local markets.

Factor-based measures are sometimes called integration measures, which slightly differ from the more straightforward correlation-based indicators. According to Pukthuanthong and Roll (2009): “perfect integration implies that the same international factors explain 100% of the broad index returns in both countries, but if country indices differ in their sensitivities to these factors, they will not exhibit perfect correlation.” Given the structure of our explanatory variables, which are based on aggregate measures of openness rather than bilateral linkages, we prefer to use an indicator of comovements based on the sensitivities of each domestic market to global market shocks.

Most of the previously defined indicators capture the exposures to the 17 initial markets, which are all developed markets except South Africa. Hence, for advanced market economies, we refer to these indicators as the interdependencies among advanced markets. On the other

hand, for emerging market economies, the previous metrics capture the sensitivity of emerging markets to advanced market shocks, also referred to as the comovements between developing and developed markets. To examine the comovements among developing markets, we construct similar measures by restricting the set of factors to emerging market shocks (1994–2018). We do not attempt to assess the exposure of advanced markets to emerging market shocks due to potential endogeneity issues. Our main results (see Section 2.5) are based on the *PCA* indicator—named *PCA-emerging* when the set of factors is restricted to developing markets. Section 2.6 controls the robustness of our findings using alternative measures of comovements.

We now analyze the long-term evolution of the comovements (i) among advanced markets, (ii) among emerging markets, and (iii) between developing and developed markets. For each market, we first test for deterministic linear trends based on Perron and Yabu (2009a). They use a Feasible Quasi Generalized Least Squares method, allowing them to measure the inference on the slope coefficient using the standard Normal distribution in the  $I(0)$  and  $I(1)$  cases. Then, we check the presence of nonlinear deterministic trends based on Perron et al. (2017). Their approach relies on a Fourier expansion with an arbitrary number of frequencies that can fit a large class of nonlinear trends. Finally, we control for structural breaks in the slope and intercept of the linear trend function following Perron and Yabu (2009b). The break dates are detected by minimizing the sum of squared residuals from regressions of the comovement series on a constant, a time trend, a level-shift dummy, and a slope-shift dummy.

The results suggest that interdependencies have increased over time for both advanced and emerging markets. We find more persuasive evidence that comovements exhibit a significant linear deterministic trend for developed markets than for developing ones (see Table 2.7). Conversely, the test of Perron et al. (2017) indicates that many emerging market interdependencies follow non-linear deterministic trends. Our analysis also reveals that the comovements (i) among emerging markets and (ii) between developing and advanced markets experienced a structural break at the end of the 2000s. On average, interdependencies peaked around 2008 for both advanced and emerging markets (see Figure 2.1 in Appendix 2.1). However, comovements among developed markets have remained at high levels since then, while interdependencies among developing markets have declined more substantially.

Furthermore, the alternative indicators of comovements tend to exhibit similar patterns apart from *ICAPM-beta*, which only captures global factor loadings. By contrast, the other indicators are also sensitive to the variance of the global factors.

#### *2.4.c. Trade and financial openness measures*

For a given country, we define trade and financial openness as the extent to which foreign (domestic) agents can and do engage in the national economy (with the rest of the world). In this sub-section, we review the major indicators of economic and financial openness proposed in the literature. We use *de jure* and *de facto* variables since both policies and flows can impact stock market comovements. Previous studies point out that information contained in *de jure* and *de facto* variables is not necessarily redundant. Indeed, policies may be strict on paper but not in practice. One of the key issues to assess the long-term impact of trade and financial links on stock market comovements is data availability. As data on bilateral links are not available over the whole period under consideration, we focus on aggregate measures (i.e., the degree of openness of each country with the rest of the world). Table 2.2 summarizes our selection of trade and financial openness indicators.

##### *i. Trade openness*

We measure the degree of trade openness based on (i) the intensity of cross-border flows of goods and services (*de facto* measures) and (ii) the state of policies regulating trade openness (*de jure* measures). The first indicator of trade openness, named *Trade-GDP*, is the sum of annual imports and exports relative to GDP. It is a standard measure that is widely available across countries and over time.

Alternatively, we use the indicator of Gygli et al. (2019), named *Trade-de-facto*, which enriches *Trade-GDP* with a component capturing the diversity of trade partners. We examine the dynamics of *Trade-GDP* and *Trade-de-facto* based on the initial cohort of 17 countries (1973–2018) in Figure 2.2 (Panel 1; see Appendix 2.2) and observe that both indicators have increased over time and exhibit similar patterns.

We also control for potential asymmetries between the long-term effects of exports and imports on stock market comovements. To this end, we construct three related measures captur-

ing the size of exports and imports relative to GDP, as well as the balance of trade (called *Exports*, *Imports*, and *Trade-Balance*, respectively).

*De jure* measures of trade openness capture the state of policies regulating trade flows. Data availability is limited for most of the measures proposed in the literature. There are a few exceptions, such as the indicator of Gwartney et al. (2018) that merges several metrics of trade tariffs and non-tariff barriers (*Trade-Barriers*). One drawback of this indicator is that data are only available at a five-year frequency between 1970 and 2000. We handle this issue using a linear interpolation framework to fill in missing data.

Alternatively, we use the indicator of Gygli et al. (2019), named *Trade-de-jure*, which merges *Trade-Barriers* with other metrics, such as free trade agreements and the income from taxes on international trade. Interestingly, the two indicators exhibit entirely different patterns from 1973 to 2016 based on the initial cohort (see Figure 2.2, Panel 2). We give more credits to *Trade-de-jure* since the index presents an upward trend, which is consistent with the process of globalization observed in the world's major economies.

## ii. *Financial openness*

Papers have measured financial openness based on (i) cross-border holdings of capital and (ii) the state of policies promoting capital liberalization. Most of the *de facto* indicators of financial openness are based on Lane and Milesi-Ferretti (2018) database, which compiles the stocks of foreign assets and liabilities at the end of each year.

First, we design a broad capital openness measure that represents the sum of all financial assets and liabilities relative to GDP (except equity portfolio investments), named *Capital-GDP*. Alternatively, we use the indicator of Gygli et al. (2019), entitled *Capital-de-facto*, which enriches the previous metric with international income payments. Saadma and Steiner (2016) also suggest a related measure that focuses on private financial openness (*Capital-Private*), which subtracts development aid and international reserves from *Capital-GDP*.

We also construct a measure that represents the inverse of the net capital positions by subtracting financial assets to liabilities (*Capital-Balance*). Finally, we build a measure based on the sum of FDI assets and liabilities relative to GDP (*FDI*). FDI refers to equity participation

above 10% of the recipient firm’s capitalization. They often take place between companies and establish effective control or influence over the decisions of the affiliate firm.

As stated above, we pay special attention to the equity market liberalization. We do not include FDI in this measure because they are less volatile than equity portfolio investments, and therefore less likely to capture the investor-based linkages mentioned above. We build a measure of equity market openness based on the sum of equity assets and liabilities relative to GDP (*Equity-GDP*). We then decompose this measure between equity assets (*Equity-Assets*) and equity liabilities (*Equity-Liabilities*), representing (i) the holdings of international stocks by domestic investors and (ii) the holdings of domestic stocks by foreign investors, respectively. Moreover, we consider the balance of equity portfolio holdings (liabilities minus assets), named *Equity-Balance*.

We show that *Capital-GDP*, *Capital-Private*, *Capital-de-facto*, *FDI*, and *Equity-GDP* all experienced a significant increase from 1973 to 2015 based on the initial cohort (see Figure 2.2, Panel 3). However, we observe that this upward trend has slowed down since the global financial crisis (2007–2009).

*De jure* measures of financial openness are mostly based on the IMF’s Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER). This database suffers from a structural break because the report was enriched with new information in 1995. On the one hand, the indicators of Chinn and Ito (2008) or Quinn (1997) only use the information available before 1995. They cover a long period but suffer from a lack of variability, which can be an issue for regressions.

On the other hand, Schindler (2009) proposes a more finely graduated measure available since 1995. Following Bekaert et al. (2016), we extend the Schindler index backward based on a panel regression procedure using the indicators of Chinn and Ito (2008) and Quinn (1997) as regressors. This indicator is entitled *Capital-AREAER*. In addition, we use the indicator of Gygli et al. (2019), named *Capital-de-jure*, which merges the measure of Chinn and Ito (2008) with other metrics based on investment restrictions and international investment agreements. Unfortunately, our indicators do not disentangle between the regulation of equity markets and

that of other capital flows.<sup>10</sup> Based on the initial cohort (1973–2016), we show that both *Capital-AREAER* and *Capital-de-jure* significantly increased from 1973 to the end of the 1990s and tend to follow close patterns (see [Figure 2.2](#), Panel 4).

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<sup>10</sup> The indicator of [Schindler \(2009\)](#) provides a decomposition by type of assets. However, it is only available since 1995 and its lack of variability can be an issue for regressions.

**Table 2.2.** Description of the explanatory variables

Data	Index name	Description	Source	Unit	Availability
Trade openness	<i>Trade-GDP</i>	(Exports + imports) / GDP	WDI World Bank	% of GDP	1973–2018
	<i>Trade-de-facto</i>	<i>De facto</i> part of the KOF trade globalization index	Gygli et al. (2019)	Index 0–1	1973–2016
	<i>Trade de facto Exports</i>	Exports / GDP	WDI World Bank	% of GDP	1973–2018
	<i>Trade de facto Imports</i>	Imports / GDP	WDI World Bank	% of GDP	1973–2018
	<i>Trade-Balance</i>	(Exports – imports) / GDP	WDI World Bank	% of GDP	1973–2018
	<i>Trade de jure Trade-Barriers</i>	Freedom to trade index, with the score for “Black Market Exchange Rates” and “controls of the movement of capital and people” being excluded	Gwartney et al. (2018)	Index 0–1	1973–2016
	<i>Trade de jure Trade-de-jure</i>	<i>De jure</i> part of the KOF trade globalization index	Gygli et al. (2019)	Index 0–1	1973–2016
Financial openness	<i>Capital-GDP</i>	Total foreign stock of capital (except equity): (Assets + Liabilities) / GDP	Lane and Milesi-Ferretti (2018)	% of GDP	1973–2015
	<i>Capital-de-facto</i>	<i>De facto</i> part of the KOF financial globalization index	Gygli et al. (2019)	Index 0–1	1973–2016
	<i>Financial de facto FDI</i>	FDI: (Assets + Liabilities) / GDP	Lane and Milesi-Ferretti (2018)	% of GDP	1973–2018
	<i>Capital-Private</i>	Private Financial Openness Index subtracting social development aid from foreign liabilities and international reserves from foreign assets.	Saadma & Steiner (2016)	% of GDP	1973–2014
	<i>Capital-Balance</i>	(Liabilities – Assets) / GDP	Lane and Milesi-Ferretti (2018)	% of GDP	1973–2015
	<i>Financial de jure Capital-AREAER</i>	Capital Account Restrictions based on AREAER dataset. Extended backward (1973-1995) using a panel regression framework based on the indicators developed by Quinn (1997) and Chinn and Ito (2008).	Schindler (2009)	Index 0–1	1973–2017
	<i>Financial de jure Capital-de-jure</i>	<i>De jure</i> part of the KOF financial globalization index	Gygli et al. (2019)	Index 0–1	1973–2016
Equity market openness <i>de facto</i>	<i>Equity-GDP</i>	Equity portfolio investments: (Assets + Liabilities) / GDP	Lane and Milesi-Ferretti (2018)	% of GDP	1973–2015
	<i>Equity-Liabilities</i>	Equity portfolio investments: Liabilities / GDP, representing the holdings of <i>domestic</i> stocks by <i>international</i> investors.	Lane and Milesi-Ferretti (2018)	% of GDP	1973–2015
	<i>Equity-Assets</i>	Equity portfolio investments: Assets / GDP, representing the holdings of <i>international</i> stocks by <i>domestic</i> investors.	Lane and Milesi-Ferretti (2018)	% of GDP	1973–2015
	<i>Equity-Balance</i>	Equity portfolio investments: (Liabilities – Assets) / GDP	Lane and Milesi-Ferretti (2018)	% of GDP	1973–2015

## 2.5. Results

This section reports our empirical results based on a sample of 47 advanced and emerging markets from 1973 to 2018. Our unbalanced panel dataset includes at least 1470 observations for each variable. It covers 47 local markets ( $N_{\min} = 17$ ;  $N_{\max} = 47$ ) and 46 annual observations ( $T_{\min} = 21$ ;  $T_{\max} = 46$ ). We find evidence of cross-sectional dependence in all the variables of our sample (see Table 2.8 in Appendix 2.3). We thus augment the ARDL and DL models with the CSA of the variables, as suggested by Chudik and Pesaran (2015). Moreover, the results of the unit root tests indicate that the variables are either  $I(0)$  or  $I(1)$ , supporting the use of the CS-ARDL and CS-DL approaches. Finally, we reject the null hypothesis of no cointegration for all the explanatory variables apart from *Trade-Balance* and *Trade-Barriers* (see Table 2.8).

Our study is motivated by preliminary analyses suggesting the existence of a long term relationship between trade and financial links and stock market comovements (see Appendix 2.3). Since the CS-ARDL and CS-DL models require a high amount of data, we cannot include all the variables in the model at the same time. Therefore, our estimation strategy consists of two steps. First, we perform univariate regressions for each explanatory variable to identify the most relevant determinants. Then, we use reduced specifications of the CS-ARDL and CS-DL models to simultaneously estimate the effects of the previously selected variables on stock market interdependencies. We report separate results for advanced and emerging markets.

### 2.5.a. Variables pre-selection

We estimate the long-term effect of each explanatory factor on stock market comovements. This first step consists in estimating successive univariate regressions based on various specifications of the CS-DL( $p_x$ ) and CS-ARDL( $p_y, p_x$ ) models, following Equations (2.1) and (2.2). We estimate the models based on the MG estimator detailed in Section 2.3.

The model specifications respectively include one, two, and three lags of the explanatory ( $1 \leq p_x \leq 3$ ) and dependent ( $1 \leq p_y \leq 3$ ) variables. Given the relatively limited size of our sample, a maximum of three lags seems appropriate to estimate the long-term parameters consistently without loss of efficiency. However, this choice also limits the ability to test more than

one determinant at a time. To handle potential omitted factor bias, we include in the model the contemporaneous values and two lags of the CSA of the variables ( $p_T = 2$ ). We follow the indicative floor of  $\sqrt[3]{T}$  suggested by Chudik and Pesaran (2015) based on the lowest individual time dimension in our panel dataset. Adding too many lags of the CSA leads to a loss of degrees of freedom and, in some cases, can also change the coefficients, as it takes out some of the variations we want to explain. On the contrary, if the number of CSA lags is not sufficient, the results may remain biased by common residual factors. After each regression, we thus test for residual cross-sectional dependence (CD-test; Pesaran, 2015).

This pre-selection step is based on our entire dataset (advanced and emerging markets). In Section 2.6.d, we check whether focusing either on developed or developing markets leads to the selection of other variables.

*i. Trade openness*

Table 2.9 reports the long-term effects of trade openness on stock market comovements (see Appendix 2.4). First, it appears that trade flows positively and significantly impact stock market comovements. In all model specifications, the effect of trade flows relative to GDP (*Trade-GDP*) is positive and significant, at least at the 5% level. The coefficients associated with *Trade-de-facto* are also all positive but significant for only two of the six specifications. We recall that the main difference between *Trade-GDP* and *Trade-de-facto* is that the latter includes a component of trade partner diversity. This adjustment severely distorts the measure in some cases (e.g., Hong Kong). Therefore, we give more weight to the results based on *Trade-GDP*.

We further examine the impact of trade openness on stock market comovements by decomposing trade flows between imports and exports. Our results suggest that both *Imports* and *Exports* significantly and positively impact stock market comovements in the long run. Interestingly, we also find that an increase in *Trade-Balance* has a significant and positive effect on stock market interdependencies. Exporting countries might be more exposed to external economic shocks than importing countries, increasing the sensitivity of the local markets to the rest of the world.

Our results regarding the impact of *de jure* trade indicators yield conflicting evidence (see Table 2.9). The long-term coefficients associated with *Trade-Barriers* are all insignificant. By contrast, we find that *Trade-de-jure* has a positive and significant influence on stock market comovements. Since previous papers have criticized *Trade-Barriers* for its lack of transparency, we give more credits to the results based on *Trade-de-jure*. Consequently, we include *Trade-GDP* and *Trade-de-jure* in the multivariate regressions (see Section 2.5.b).

*ii. Broad financial openness*

The results reported in Table 2.10 (see Appendix 2.4) reveal that cross-border capital holdings do not have a significant impact on stock market comovements. The long-term parameters associated with *Capital-GDP* are insignificant. Moreover, the results only provide limited evidence that *Capital-de-facto* impacts stock market interdependencies in the long run.

Our results also highlight that FDI holdings do not affect stock market comovements. In the same way, we find no effect of *Capital-Private* and *Capital-Balance* on the rise in stock market interdependencies. Overall, these findings suggest that capital account openness does not create a channel for shock propagation across local equity markets.

Then, we examine the long-term effect of the policies regulating capital flows on stock market comovements. Unlike *de facto* variables, *de jure* financial openness positively and significantly impacts market interdependencies over the long term. We include *Capital-de-jure* rather than *Capital-AREAER* in the main regressions (see Section 2.5.b), as we reject twice the null hypothesis of error cross-sectional independence based on *Capital-AREAER*.

*iii. Equity market openness*

Finally, we analyze the long-term effects of equity market openness on stock market interdependencies (see Table 2.10). We find that *Equity-GDP* has a positive and significant impact on stock market comovements. We also examine whether the rise in equity market comovements is mostly driven by the holdings of (i) international stocks by domestic investors (*Equity-Assets*) or (ii) domestic stocks by foreign investors (*Equity-Liabilities*). Our findings suggest that *Equity-Liabilities* is the only relevant determinant of the changes in stock market interdependencies over the long term.

On the contrary, all the parameters related to *Equity-Assets* are insignificant. Interestingly, the long-term impact of *Equity-Assets* on stock market interdependencies is negative. This outcome suggests that the purchase of foreign stocks by domestic investors tends to reduce the comovements among stock markets. It is in line with the findings of Adler et al. (2016), who indicate that asset repatriation during episodes of global uncertainty may offset the seller flows from foreign investors.

### 2.5.b. *The determinants of the rise in stock market comovements*

The previous results are robust to the presence of common omitted factors. However, univariate regressions cannot control for common components in the explanatory variables, such as a parallel increase in trade and financial links. For this reason, we use the variables identified in the previous sub-section and test them together in a multivariate framework.

We simultaneously examine the influences of trade flows (*Trade-GDP*), trade openness policies (*Trade-de-jure*), domestic equity holdings by international investors (*Equity-Liabilities*), and financial openness policies (*Capital-de-jure*). Changes in *Equity-Liabilities* depend both on aggregate inflows and market returns (i.e., valuation effect). To ensure that *Equity-Liabilities* captures the impact of aggregate inflows, we include the size of the market capitalization relative to GDP (*MktCap-GDP*) in the model as a control variable for the valuation effect. This variable also accounts for the level of financial development, which is one of the main determinants of stock market comovements, according to Kim et al. (2005).

Previous studies have indicated that investors tend to consider emerging markets as a separate asset class (e.g., Bekaert and Harvey, 2014). Hence, the roots of the rise in equity market comovements may be different for advanced and emerging market economies. To test this hypothesis, we report separate results for the comovements (i) among advanced markets, (ii) among emerging markets, and (iii) between developing and developed markets.

Since our sample is relatively small and the CS-ARDL and CS-DL approaches are data-intensive models, we use a single lag of the variables ( $p_y = p_x = 1$ ) and augment the models with the contemporaneous values of the CSA ( $p_T = 0$ ). In all cases, we compute the CSA based on the entire sample (i.e., 47 markets). After each regression, we test for residual cross-sectional dependence (CD-test; Pesaran, 2015). We also control, for every specification, that the MG

estimator is appropriate using the HAC consistent test of slope homogeneity (MG-test; Blomquist and Westerlund, 2013).

*i. Comovements among advanced markets*

We first examine the determinants of the comovements among advanced markets (see Table 2.3). The results indicate that the rise in developed market interdependencies mainly stems from increased trade openness. The parameters associated with *Trade-GDP* are positive and significant for all specifications except one. A 1% rise in *Trade-GDP* leads to a 0.447–0.740% increase in stock market interdependencies in the long run, which is consistent with the findings based on univariate regressions. Moreover, the easing of trade openness policies seems to have a positive impact on stock market interdependencies over the long term. The coefficients associated with *Trade-de-jure* are positive (between 0.695 and 1.394) and significant for all but the fifth and eighth specifications.

On the other hand, the coefficients associated with *Equity-Liabilities* are all negative and mostly insignificant, indicating that increased foreign equity holdings are not at the root of the rise in the comovements among advanced markets. In the same way, the easing of capital openness policies (*Capital-de-jure*) does not appear to be a relevant channel for shock transmission across advanced stock markets.

Since market returns can be divided into a cash flow and a discount rate component, our results highlight that increased dependence between cash flows is the primary determinant of the growing interdependencies among advanced markets. We accept the null hypothesis of weak cross-sectional dependence in the residuals, confirming that the results are robust to common omitted factors. We also reject the assumption of slope homogeneity for all specifications, which indicates that the MG estimator is appropriate. Finally, we find that the speed of adjustment to the long-term relationship is always significant and close to  $-1$ , implying that deviations from the equilibrium are corrected by the following year.

**Table 2.3.** Determinants of the comovements among advanced markets

<i>Panel A: CS-ARDL with one lag and contemporaneous CSA</i>											
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
<i>Trade-GDP</i>		0.454* (0.251)		0.740*** (0.209)		0.690** (0.272)		0.520** (0.230)	0.635** (0.260)	0.610* (0.343)	0.704** (0.322)
<i>Trade-de-jure</i>	1.025** (0.404)			0.695*** (0.265)	0.402 (0.380)		0.946* (0.494)	0.191 (0.344)	1.362*** (0.472)		1.394*** (0.477)
<i>Equity-Liabilities</i>		-0.883* (0.485)	-0.616 (0.573)		-0.435 (0.786)		-0.345 (0.787)	-0.485 (0.603)		-0.904 (0.573)	-0.710 (0.613)
<i>Capital-de-jure</i>	0.151 (0.331)		0.266 (0.256)			0.401 (0.327)	-0.172 (0.291)		-0.325 (0.385)	0.092 (0.388)	-0.463 (0.515)
<i>MktCap-GDP</i>		0.568*** (0.139)	0.534*** (0.190)		0.387 (0.282)		0.318 (0.273)	0.359* (0.208)		0.475** (0.211)	0.273 (0.242)
N	914	884	884	914	884	914	884	884	914	884	884
n	24	24	24	24	24	24	24	24	24	24	24
Tbar	39.51	38.28	38.28	39.51	38.28	39.51	38.28	38.28	39.51	38.28	38.28
ECT	-0.91***	-0.95***	-0.91***	-0.94***	-0.94***	-0.91***	-0.95***	-0.99***	-0.95***	-0.97***	-1.01***
MG-test	9.41***	17.58***	15.17***	10.97***	13.78***	12.74***	8.85***	7.99***	13.79***	14.93***	5.54***
CD-test	-0.20	-0.03	1.06	-0.68	-0.73	1.15	-0.55	-1.16	-0.74	-0.04	-1.05
<i>Panel B: CS-DL with one lag and contemporaneous CSA</i>											
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
<i>Trade-GDP</i>		0.387 (0.247)		0.740*** (0.212)		0.641*** (0.247)		0.447* (0.249)	0.635** (0.260)	0.546* (0.321)	0.640* (0.328)
<i>Trade-de-jure</i>	0.935** (0.364)			0.726*** (0.242)	0.519 (0.362)		0.856* (0.450)	0.357 (0.333)	1.362*** (0.472)		1.123*** (0.429)
<i>Equity-Liabilities</i>		-0.838* (0.455)	-0.502 (0.542)		-0.247 (0.668)		-0.246 (0.704)	-0.314 (0.544)		-0.931* (0.521)	-0.708 (0.577)
<i>Capital-de-jure</i>	0.162 (0.346)		0.270 (0.258)			0.402 (0.314)	-0.139 (0.295)		-0.325 (0.385)	0.040 (0.322)	-0.384 (0.485)
<i>MktCap-GDP</i>		0.532*** (0.135)	0.467*** (0.180)		0.281 (0.233)		0.264 (0.244)	0.288 (0.184)		0.494*** (0.191)	0.305 (0.230)
N	914	884	884	914	884	914	884	884	914	884	884
n	24	24	24	24	24	24	24	24	24	24	24
Tbar	39.51	38.28	38.28	39.51	38.28	39.51	38.28	38.28	39.51	38.28	38.28
MG-test	11.59***	13.65***	25.41***	12.78***	9.95***	14.04***	13.78***	7.99***	12.30***	10.38***	12.23***
CD-test	-0.25	-0.17	1.21	-0.63	-0.65	1.22	-0.45	-1.38	-0.88	-0.31	-1.42

*Notes:* This table simultaneously analyzes the long-term impacts of trade and financial links on the comovements among advanced markets, using multivariate regressions. We add a control variable that captures the valuation effect and the level of financial development (*MktCap-GDP*). All estimations are based on the MG estimator. We test the null hypothesis of slope homogeneity (MG-test) for each specification. After each regression, we also test for cross-sectional dependence (CD-test). Standard errors are in parentheses. \*, \*\*, and \*\*\* indicate significance at the 10, 5, and 1% level, respectively.

ii. *Comovements among emerging markets*

We study the determinants of the rise in comovements among emerging markets (see Table 2.4). The results are based on *PCA-emerging*, which captures the exposure of each developing market to a set of global factors derived from emerging market data. We find evidence that the purchase of developing stocks by foreign investors has a positive and significant impact on stock market interdependencies for all specifications. A 1% increase in *Equity-Liabilities* leads to a rise of 3.052–7.380% in the comovements among emerging markets in the long run. The results are robust to the inclusion of *MktCap-GDP*, confirming that *Equity-Liabilities* captures aggregate inflows rather than a valuation effect.

On the contrary, our findings point out that *Trade-GDP*, *Trade-de-jure*, and *Capital-de-jure* do not impact the comovements among emerging markets. This result indicates that neither the increase of trade flows nor the liberalization of trade and financial policies contributes to the rise in developing market comovements. Table 2.4 also reports a negative impact of *MktCap-GDP* on the dependent variable. The long-term coefficients are all negative (between  $-0.505$  and  $-1.833$ ) and significant for 5 out of the 14 specifications. This outcome supports the idea that financial development and positive market returns can help reduce the propagation of shocks between emerging markets.

We accept the null hypothesis of weak cross-sectional dependence for 16 out of the 22 specifications. This fact globally confirms the robustness of the results to common omitted factors. However, the MG-tests only reject the null hypothesis of slope homogeneity for 14 out of the 22 regressions. In addition, the error correction coefficient is inferior to  $-1$ . These findings suggest that the number of explanatory variables could be too large with respect to the time dimension to use the MG estimator. We thus test the robustness of the results to alternative estimators in Section 2.6.c.

**Table 2.4.** Determinants of the comovements among emerging markets

<i>Panel A: CS-ARDL with one lag and contemporaneous CSA</i>											
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
<i>Trade-GDP</i>		0.127 (0.340)		0.098 (0.280)		0.006 (0.231)		0.030 (0.520)	-0.015 (0.309)	0.077 (0.414)	-1.817 (2.032)
<i>Trade-de-jure</i>	0.477 (0.315)			0.743** (0.357)	0.190 (0.416)		0.178 (0.565)	-0.122 (0.721)	0.596 (0.591)		0.989 (1.094)
<i>Equity-Liabilities</i>		4.188*** (1.330)	3.795*** (1.233)		3.052*** (1.087)		3.898*** (1.374)	6.007** (2.459)		4.411** (2.145)	5.757*** (2.057)
<i>Capital-de-jure</i>	0.341 (0.247)		0.001 (0.277)			0.305 (0.195)	-0.618** (0.277)		0.054 (0.307)	-0.071 (0.330)	0.105 (0.725)
<i>MktCap-GDP</i>		-0.190 (0.415)	-0.492 (0.321)		-0.505* (0.285)		-0.722** (0.334)	-1.514 (1.259)		-0.254 (0.593)	-1.292** (0.608)
N	502	478	479	500	479	500	479	478	500	478	478
n	23	23	23	23	23	23	23	23	23	23	23
Tbar	21.83	20.79	20.83	21.75	20.83	21.75	20.83	20.79	21.75	20.79	20.79
ECT	-1.11***	-1.20***	-1.14***	-1.18***	-1.23***	-1.07***	-1.29***	-1.26***	-1.15***	-1.27***	-1.39***
MG-test	2.02**	4.26***	0.41	8.49***	5.59***	8.94***	-0.53	3.04***	1.14	0.02	4.69***
CD-test	0.11	1.64	-0.05	3.24***	1.40	0.78	1.57	0.60	1.65	-0.08	2.89***
<i>Panel B: CS-DL with one lag and contemporaneous CSA</i>											
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
<i>Trade-GDP</i>		0.073 (0.342)		0.181 (0.282)		-0.040 (0.220)		0.106 (0.368)	0.001 (0.301)	0.230 (0.416)	0.021 (0.733)
<i>Trade-de-jure</i>	0.449 (0.337)			0.458 (0.310)	0.112 (0.352)		0.355 (0.572)	-0.288 (0.489)	0.349 (0.556)		-0.470 (0.853)
<i>Equity-Liabilities</i>		3.542*** (1.124)	3.666*** (1.105)		4.139*** (1.199)		3.435*** (1.300)	4.921*** (1.710)		3.131* (1.635)	7.380*** (2.256)
<i>Capital-de-jure</i>	0.300 (0.287)		-0.043 (0.247)			0.258 (0.205)	-0.433 (0.378)		0.126 (0.322)	-0.008 (0.346)	-0.042 (0.677)
<i>MktCap-GDP</i>		-0.109 (0.438)	-0.448 (0.303)		-0.482 (0.307)		-0.571* (0.344)	-0.772 (0.696)		-0.049 (0.509)	-1.833** (0.787)
N	502	478	479	500	479	500	479	478	500	478	478
n	23	23	23	23	23	23	23	23	23	23	23
Tbar	21.83	20.79	20.83	21.75	20.83	21.75	20.83	20.79	21.75	20.79	20.79
MG-test	7.63***	1.50	2.12**	6.44***	3.71***	5.71***	-1.07	2.54**	4.43***	-1.12	-1.57
CD-test	0.53	1.75*	-0.51	3.02***	1.47	0.72	-0.09	1.70*	1.34	-0.07	3.67***

*Notes:* This table simultaneously analyzes the long-term impacts of trade and financial links on emerging market interdependencies, using multivariate regressions. We add a control variable that captures the valuation effect and the level of financial development (*MktCap-GDP*). All estimations are based on the MG estimator. We test the null hypothesis of slope homogeneity (MG-test) for each specification. After each regression, we also test for cross-sectional dependence (CD-test). Standard errors are in parentheses. \*, \*\*, and \*\*\* indicate significance at the 10, 5, and 1% level, respectively.

*iii. Comovements between emerging and advanced markets*

We investigate the determinants of the comovements between emerging and advanced markets. The results, presented in Table 2.5, are based on *PCA*, which measures the sensitivities of each developing market to the major equity markets. Again, we find evidence that the rise in comovements between developing and developed markets is due to the purchase of emerging stocks by international investors. The long-term effect of *Equity-Liabilities* is positive for all specifications (between 2.395 and 6.547) and significant at the 5% level for 10 of the 14 regressions. The results are also robust to the inclusion of *MktCap-GDP*.

On the contrary, the parameters associated with *Trade-GDP* are all small and insignificant, which indicates that increased trade links do not play a significant role in the rise in interdependencies between emerging and advanced markets. Besides, while the results provide some evidence that the easing of trade and financial policies positively and significantly impacts the sensitivities of emerging markets to international market shocks, the coefficients systematically become small and insignificant when *Equity-Liabilities* is included in the model.

According to the MG-test, the individual coefficients are heterogeneous for most specifications. In all cases, we accept the null hypothesis of weak cross-sectional dependence in the residuals. Finally, we find that the speed of adjustment to the long-term relationship is always fast and significant.

**Table 2.5.** Determinants of the comovements between emerging and advanced markets

Variables	<i>Panel A: CS-ARDL with one lag and contemporaneous CSA</i>										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
<i>Trade-GDP</i>		0.045 (0.299)		0.008 (0.218)		-0.079 (0.188)		0.007 (0.561)	-0.093 (0.214)	0.042 (0.298)	0.354 (0.419)
<i>Trade-de-jure</i>	0.611 (0.377)			0.642*** (0.206)	0.075 (0.268)		0.009 (0.444)	-0.417 (0.451)	0.740* (0.440)		-0.458 (0.826)
<i>Equity-Liabilities</i>		1.893 (1.369)	2.498** (1.195)		2.932** (1.270)		4.206*** (1.519)	4.973 (3.268)		1.718 (1.692)	4.995** (2.116)
<i>Capital-de-jure</i>	0.653** (0.272)		0.251 (0.260)			0.543*** (0.165)	-0.191 (0.467)		0.639** (0.312)	0.316 (0.287)	0.0371 (0.913)
<i>MktCap-GDP</i>		-0.103 (0.351)	-0.185 (0.296)		-0.553 (0.535)		-0.553 (0.579)	-1.824 (2.043)		0.214 (0.442)	-0.827 (1.025)
N	583	559	560	581	560	581	560	559	581	559	559
n	23	23	23	23	23	23	23	23	23	23	23
Tbar	26.23	25.24	25.27	26.18	25.27	26.18	25.27	25.24	26.18	25.24	25.24
ECT	-1.08***	-1.11***	-1.09***	-1.08***	-1.13***	-1.04***	-1.19***	-1.20***	-1.12***	-1.18***	-1.21***
MG-test	1.29	4.12***	4.81***	5.35***	2.48**	16.58***	8.40***	3.43***	2.27**	3.73***	1.38
CD-test	-1.00	-0.77	-1.26	-1.11	0.74	-1.53	0.26	1.33	-0.38	-1.02	0.45

Variables	<i>Panel B: CS-DL with one lag and contemporaneous CSA</i>										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
<i>Trade-GDP</i>		0.023 (0.263)		0.075 (0.201)		-0.077 (0.187)		0.042 (0.385)	-0.133 (0.192)	0.072 (0.287)	0.592 (0.638)
<i>Trade-de-jure</i>	0.699* (0.369)			0.630*** (0.182)	0.113 (0.235)		0.164 (0.431)	-0.368 (0.301)	0.951** (0.434)		-0.679 (0.625)
<i>Equity-Liabilities</i>		2.395* (1.241)	2.619** (1.090)		3.826*** (1.271)		3.324** (1.318)	4.852** (2.361)		2.013 (1.650)	6.547*** (2.466)
<i>Capital-de-jure</i>	0.654** (0.290)		0.318 (0.268)			0.532*** (0.179)	0.220 (0.425)		0.558* (0.297)	0.286 (0.336)	0.028 (0.643)
<i>MktCap-GDP</i>		-0.118 (0.407)	-0.278 (0.399)		-0.546 (0.550)		-0.502 (0.635)	-1.126 (1.395)		0.047 (0.507)	-1.657 (1.406)
N	583	559	560	581	560	581	560	559	581	559	559
n	23	23	23	23	23	23	23	23	23	23	23
Tbar	26.23	25.24	25.27	26.18	25.27	26.18	25.27	25.24	26.18	25.24	25.24
MG-test	5.77***	4.61***	6.03***	19.49***	4.68***	22.33***	20.01***	4.61***	20.67***	2.46***	4.03***
CD-test	-1.39	-1.26	-1.27	-1.13	-0.32	-1.45	-0.96	-0.37	-1.10	-1.34	-1.12

*Notes:* This table simultaneously analyzes the long-term impacts of trade and financial links on the comovements between emerging and advanced markets, using multivariate regressions. We add a control variable that captures the valuation effect and the level of financial development (*MktCap-GDP*). All estimations are based on the MG estimator. We test the null hypothesis of slope homogeneity (MG-test) for each specification. After each regression, we also test for cross-sectional dependence (CD-test). Standard errors are in parentheses. \*, \*\*, and \*\*\* indicate significance at the 10, 5, and 1% level, respectively.

## 2.6. Robustness tests

### 2.6.a. Reverse causality

According to the portfolio theory, investors should seek diversification opportunities and invest in the stock markets that are the least interdependent with their home market. Therefore, all else being equal, the least interconnected markets should attract more foreign equity flows.

This assumption raises questions about the direction of the relationship between foreign equity holdings and stock market comovements. Yet, most of the existing studies use standard panel methods that do not adequately address this issue.

We examine the potential impact of stock market comovements (*PCA*) on foreign equity holdings (*Equity-Liabilities*) based on different specifications of the CS-ARDL model. The CS-ARDL model is robust to potential feedback effects, as long as we include enough lags of the dependent and explanatory variables in the model. Based on advanced markets, we find a positive but non-significant effect of *PCA* on *Equity-Liabilities* (see Table 2.6). Regarding developing markets, the results show weak evidence that the level of stock market comovements impacts foreign equity holdings. The coefficients associated with *PCA-emerging* are positive and significant at the 10% level in the first and second specifications. However, the effect becomes insignificant when we augment the CS-ARDL model with additional lags.

It is worth noting that our analysis focuses on aggregate flows rather than bilateral links. Therefore, our findings do not necessarily contradict the conclusions of previous studies that find a significant and negative relationship between equity market interdependencies and equity flows based on bilateral data (e.g., Coeurdacier and Guibaud, 2011).

**Table 2.6.** Testing for reverse causality between stock market comovements and equity holdings

Panel A: Advanced markets			
	CS-ARDL (1,1)	CS-ARDL(2,2)	CS-ARDL(3,3)
<i>PCA</i>	0.818 (0.826)	-1.053 (1.111)	0.128 (0.702)
Observations	861	860	836
ECT	-0.292***	-0.338***	-0.379***
CD-test	26.92***	25.94***	23.55***
Panel B: Emerging markets			
	CS-ARDL (1,1)	CS-ARDL(2,2)	CS-ARDL(3,3)
<i>PCA</i>	0.039 (0.027)	-0.234 (0.244)	-0.003 (0.044)
Observations	537	537	514
ECT	-0.530***	-0.494***	-0.687***
CD-test	-0.619	-0.323	1.723*
<i>PCA-emerging</i>	0.052* (0.027)	0.345* (0.189)	0.607 (0.399)
Observations	456	456	433
ECT	-0.696***	-0.653***	-0.644***
CD-test	-2.350**	-0.848	0.977

*Notes:* The results are based on the CS-ARDL model with one, two, and three lags of the dependent and independent variables. We use the MG estimator for all specifications. To handle potential omitted factor bias, we include in the model the contemporaneous values and two lags of the CSA of the variables. We also test for cross-sectional dependence (CD-test) after each regression. Standard errors are in parentheses. The signs \*, \*\*, and \*\*\* indicate significance at the 10, 5, and 1% level, respectively.

### 2.6.b. Alternative measures of stock market comovements

In this sub-section, we test the robustness of the results to the alternative measures of comovements defined in Section 2.4.b (*PCA-local-currency*, *PCA-local-sector*, *PCA-all-markets*, *ICAPM-R<sup>2</sup>*, *ICAPM-beta*, *Correlation*).

We first test a subset of our main regressors based on univariate regressions (see Table 2.11). We broadly confirm the results reported in Section 2.5.a, although we find little or no evidence that trade openness significantly impacts *ICAPM-beta* and *PCA-local-sector*. Then, based on multivariate regressions, we report separate results for the comovements (i) among advanced markets, (ii) among emerging markets, and (iii) between developing and developed markets (see Table 2.12). For each alternative measure, Specification 1 tests the two most likely regressors (as defined in Section 2.5), Specification 2 includes all regressors, and Specification 3 adds the control variable (*MktCap-GDP*).

Our main findings are globally robust to the use of alternative comovement measures. However, the size and the degree of significance of the coefficients tend to vary from one indicator to another. There are several possible explanations for this phenomenon. First, the dependent variables focus on different aspects of stock market comovements. For example, while the baseline index (*PCA*) focuses on the exposures of each local stock market to the major equity markets, *PCA-all-markets* can potentially capture the growing influence of emerging market shocks. Second, including the CSA of all the variables (to control for common omitted factors) can change the coefficients, as it takes out some of the variations we want to explain. Hence, if some comovement indicators display higher cross-sectional dependence than others, the inclusion of the CSA can potentially affect the results.

### *2.6.c. Alternative estimators*

Our main results are based on the MG estimator, which is consistent whether the individual coefficients are homogeneous or heterogeneous. Based on the test of Blomquist and Westerlund (2013), we confirm that the estimates tend to vary across individuals, indicating that the MG estimator is appropriate for our study. However, we cannot always reject the null hypothesis of homogeneous coefficients for the interdependencies among developing markets (see Table 2.4). We thus check the robustness of the results using the pooled mean group (PMG) and the dynamic fixed effects (DFE) estimators. The PMG estimator constrains the long-run coefficients to be equal but allows the short-term estimates to vary across individuals. The DFE estimator pools all the coefficients, apart from the intercepts.

Based on both the PMG and the DFE estimators, we confirm that international investors play a critical role in the rising comovements among emerging markets (see Table 2.14 in Appendix 2.6). It is worth noting that the coefficients based on the PMG and DFE estimators tend to be smaller than those based on the MG estimator. This result suggests that the time dimension ( $T=21$ ) might be too small to estimate individual coefficients consistently with the MG estimator. Likewise, while the error correction term tends to be inferior to  $-1$  based on the MG estimator, the coefficient is between 0 and  $-1$  using the DFE estimator.

As the MG estimator is sensitive to outliers in the individual estimates, we also test the robustness of our results by computing outlier-robust averages of the country-specific coefficients

instead of unweighted means. This approach, based on a robust regression algorithm, weights each observation according to its distance to the mean of the other estimates. The results, reported in Table 2.13, globally confirm our main findings.

#### 2.6.d. *Univariate regressions for advanced and emerging markets*

In Section 2.5, we select the main regressors using univariate regressions based on the entire sample. This approach allows us to compare the determinants of developed and developing market comovements based on a common set of regressors. In this sub-section, we check if other variables would have been selected by focusing either on advanced or emerging markets. First, we confirm that *de facto* trade openness variables only drive the comovements among advanced markets (see Table 2.15). Interestingly, the analysis also provides some evidence that *de facto* financial links impact developed market interdependencies (see Table 2.16).

Moreover, the results indicate that foreign equity holdings have positive effects on both advanced and emerging market comovements. However, once we control for the valuation effect (using *MktCap-GDP*), we confirm that the impact of *Equity-Liabilities* is only significant for emerging markets (see Table 2.17). To test the robustness of this finding, we also create a new variable, *Equity-MktCap*, that divides foreign equity holdings by market capitalization. The coefficient associated with this variable is positive and significant only for the interdependencies among emerging markets.

#### 2.6.e. *Eliminate tax havens*

Some individuals, such as Honk Kong, Ireland, Luxembourg, Netherlands, and Singapore, are tax-havens. These countries tend to have higher values in terms of capital holdings relative to GDP compared to the rest of the database (see Table 2.8). Moreover, the dynamics of the aggregate capital flows in tax-havens might display different patterns compared to the rest of the sample. Therefore, we control the robustness of our results to the exclusion of the tax-havens from the database. We only recompute the results for advanced markets since all tax-havens in the dataset belong to this category. The results, presented in Table 2.18 (see Appendix 2.7), are very similar to those based on the entire set of developed markets (see Table 2.3). This

analysis confirms that trade openness is the main determinant of the rise in comovements among advanced markets.

## 2.7. Contributions of the chapter

We compare our findings with the existing literature and examine the extent to which our analysis sheds new light on the determinants of stock market comovements. We also discuss the implications of our results on policy issues.

For advanced markets, we show that the strengthening of trade flows and the liberalization of trade policies drive the rise in market interdependencies. On the other hand, we find no evidence that the increase in cross-border equity holdings and the deregulation of capital flows impact equity market comovements. These findings confirm the conclusions of [Forbes and Chinn \(2004\)](#), who note that direct trade links are the primary determinant of stock market comovements. We also complement their study, as [Forbes and Chinn \(2004\)](#) do not distinguish between advanced and emerging markets and only focus on the determinants of the short-term changes in stock market comovements.

By contrast, our results tend to contradict those of [Baele and Soriano \(2010\)](#), which indicate that the exposure of European stock markets to US market shocks is mainly associated with financial openness. Our analysis also contrasts with the conclusions of [Anagnostopoulos et al. \(2019\)](#), as we find little evidence that foreign direct investments impact stock market interdependencies. This discrepancy may be due to differences in samples since their paper focuses on bilateral linkages among six advanced markets.

Our findings are globally consistent with the literature examining the effect of trade and financial openness on business cycle synchronization. [Frankel and Rose \(1998\)](#) find empirical evidence that trade linkages increase the correlation between business cycles. By contrast, [Bordo and Helbling \(2003\)](#) show that financial ties do not affect business synchronization. Besides, in line with [Kim et al. \(2005\)](#), we find some evidence that financial development, represented by the size of the market capitalization relative to GDP, drives the rise in interdependencies among developed markets. This finding may suggest that financial development increases market liquidity, allowing stock prices to reflect global information more rapidly.

Regarding developing markets, we provide evidence that the growing presence of international shareholders is the primary determinant of the rise in comovements. Our results enrich the findings of [Quinn and Voth \(2008\)](#), which cannot distinguish which element of the capital account openness is the most relevant to explain the evolutions of stock market interdependencies. [Bekaert and Harvey \(2000\)](#) argue that equity market liberalization led to a one-time adjustment in stock market comovements. Conversely, we show that the rise in the participation of foreign investors in emerging stocks has been a gradual phenomenon (see [Figure 2.3](#) in [Appendix 2.2](#)) with a long-term impact on stock market comovements.

This chapter contributes to the literature on the benefits and drawbacks associated with equity market liberalization and international equity flows. On the one hand, previous studies highlight that equity market liberalization can improve risk-sharing benefits ([Obsfeld, 1994](#)), lower the cost of capital ([Bekaert and Harvey, 2000](#)), and spur investments and growth ([Henry, 2000](#); [Bekaert et al., 2005](#)). On the other hand, equity flows tend to increase financial vulnerabilities and amplify domestic distortions (see [IMF, 2012](#)). Our contribution is to show that (aggregate) equity inflows in emerging market economies have led to increased comovements (i) among emerging markets and (ii) between developing and developed markets. Our findings thus support the idea that the very search for investment opportunities in developing markets leads to a decline in the benefits of international diversification. This effect is a concern for investors and should be taken into account when assessing the pros and cons of equity market liberalization.

In this regard, we examine whether the magnitude of the impact of international shareholders on equity market interdependencies can deter investors from seeking diversification in emerging markets. The results show that a 1% increase in foreign equity holdings (relative to GDP) leads to a rise in emerging market comovements ranging between 1 and 7% in the long run (depending on the estimator and the number of variables included in the model). This effect is economically significant and may require regulatory intervention. The comovements (i) among developing markets and (ii) between emerging and advanced markets peaked at 60% during the global financial crisis (2007–2009) before declining and then stabilizing around 35% during the 2010s (see [Figure 2.1](#) in [Appendix 2.1](#)). This finding is in line with the fact that the process of financial liberalization has been on hold since the global financial crisis. Consequent-

ly, the comovements (i) among emerging markets and (ii) between developing and developed markets remain significantly lower than those among advanced markets, indicating that international investors can still benefit from investing in emerging markets.

Our study also provides additional evidence on the role of foreign shareholders on stock market comovements. Previous work examines this issue in the short run based on (i) the returns of investible and non-investible stocks in emerging markets (Boyer et al., 2006; Bae et al., 2012), (ii) firm-level institutional ownership (Bartram et al., 2015; Farias and Ferreira, 2017), (iii) the inclusion of stocks in major indices (Claessens and Yafeh, 2013, among others), or (iv) mutual fund data (Jotikasthira et al., 2012; Raddatz et al., 2017). Our analysis shows that there are a cointegration and a long-term relationship between foreign equity holdings and equity market interdependencies. Hence, our results can help explain the four-decade-decline in the relative benefits of international portfolio diversification.

As mentioned above, international investors can impact stock market comovements through various channels. First, the openness of domestic equity markets to foreign investors can affect the cost of capital (see Bekaert and Harvey, 2000). However, since capital account openness seems to have no impact on stock market comovements, we doubt that the influence of equity financing on companies could be large enough to fuel the rise in stock market comovements. Indeed, the amount of cross-border equity flows is quite small compared to the other types of capital flows (see Table 2.8, Appendix 2.3). Second, foreign equity investments can improve informational efficiency in local stock markets (Bae et al., 2012). Therefore, *Equity-Liabilities* might capture the increasing effect of trade and financial ties on stock market comovements. Third, the theoretical literature examines several non-fundamental linkages through which foreign investors can influence stock market comovements (see Section 2.1). Therefore, our findings suggest that part of the rise in emerging market interdependencies is the result of non-fundamental investor-based linkages. We believe that this is a potential risk to financial stability, which might call for international regulation of equity flows.

## 2.8. Conclusion

This chapter aims to uncover the mechanisms underlying the rise in international stock return comovements over the past four decades. Following the hypotheses of the theoretical literature, we assess the long-term impact of increased trade and financial links on the interdependencies among equity markets. We also pay special attention to the role of international shareholders in the evolution of stock market comovements.

We find evidence that the determinants of the rise in stock market comovements are different in advanced and emerging market economies. Our results reveal that the surge in interdependencies among developed markets has been driven by increased trade openness. By contrast, the increase in comovements (i) among emerging markets and (ii) between developing and advanced markets is the result of the purchase of domestic stocks by foreign investors.

This result is a significant issue for investors, as the rise in stock market interdependencies limits the benefits of international diversification. Therefore, the very search for investment opportunities in emerging markets seems to cause a decline in international diversification. Since foreign shareholders can theoretically transmit shocks across markets regardless of the underlying trade and financial links between countries, our findings also suggest that part of the rise in emerging market interdependencies stems from non-fundamental investor-based linkages. This result is a concern for regulators, as non-fundamental linkages can undermine the stability of the financial system by facilitating the propagation of shocks between countries.

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## Appendices

### Appendix 2.1. The dynamics of stock market comovements

**Table 2.7.** Trends in comovement measures

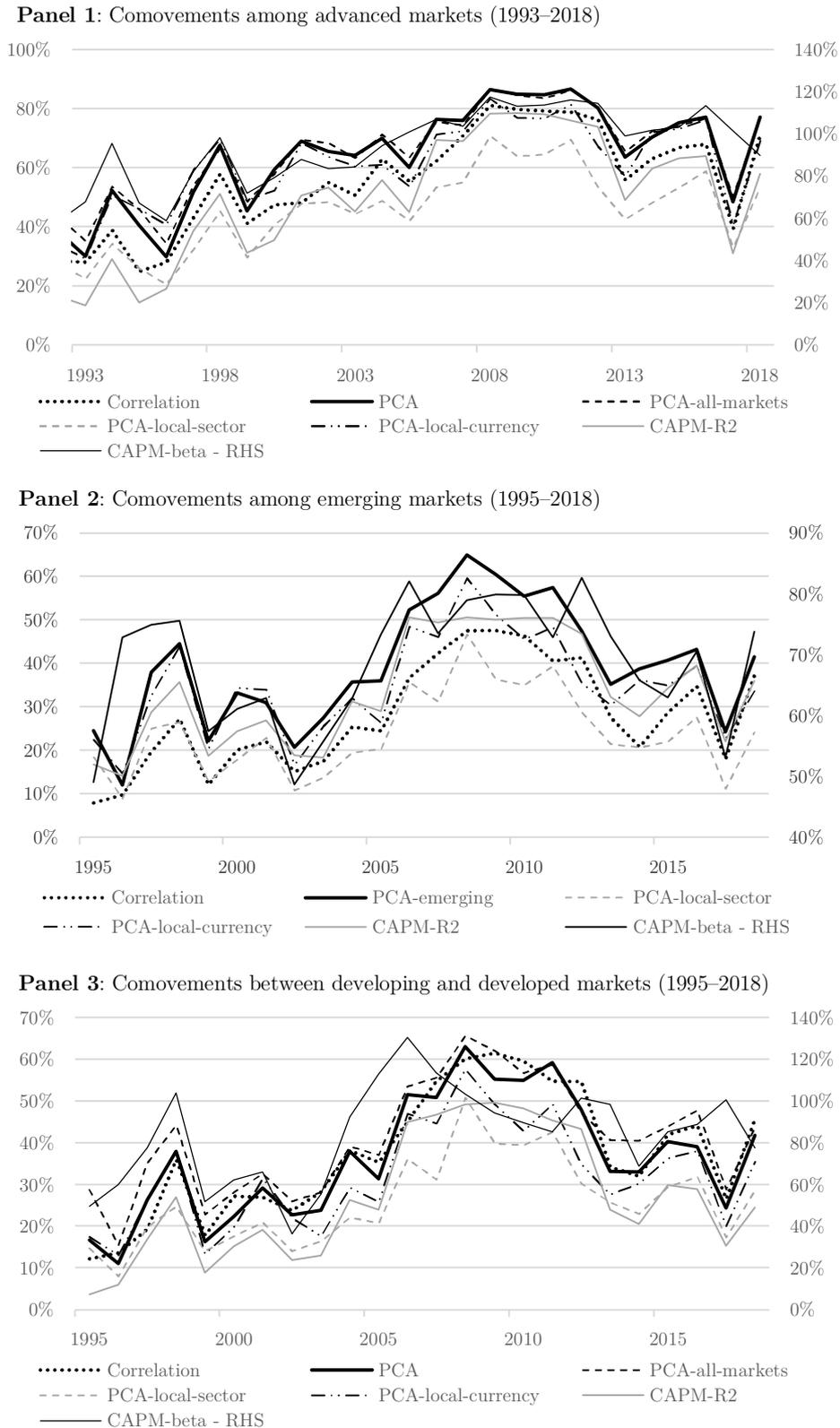
Country	PY (2009a)		PSY (2017)	PY (2009b)	
	Annual trend (%)	<i>t-stat</i>	<i>Wald-stat</i>	Break date	$W_{RQF}$
Panel A: Comovements among advanced markets ( <i>PCA</i> )					
Australia	1.16**	(2.35)	(0.26)	2005	(0.79)
Austria	0.77	(1.22)	(0.33)	2003	(2.58)
Belgium	0.31	(0.55)	(1.30)	1999	(1.14)
Canada	0.72**	(2.19)	(0.04)	2007	(0.28)
Denmark	1.26***	(2.59)	(0.10)	2005**	(3.93)
Finland	2.31**	(2.41)	(3.94)	2005***	(11.54)
France	1.47***	(5.00)	(1.66)	1997	(0.87)
Germany	0.98***	(4.07)	(1.40)	1999	(2.40)
Hong Kong	1.08***	(4.61)	(4.23)	1986	(0.83)
Ireland	0.43	(0.97)	(0.50)	2005***	(5.37)
Israel	2.20***	(2.87)	(1.08)	2012	(1.21)
Italy	1.14*	(1.65)	(1.56)	1997	(1.84)
Japan	1.25	(1.55)	(1.89)	1991**	(3.24)
Luxembourg	-0.93	(-0.56)	(19.59)***	2007	(2.31)
Netherlands	0.72***	(4.02)	(0.51)	1999	(0.48)
New Zealand	0.55	(0.56)	(5.09)*	2007***	(12.01)
Norway	0.46	(0.53)	(2.07)	2003***	(7.13)
Portugal	1.91*	(1.78)	(8.28)**	2007**	(3.35)
Singapore	0.99***	(3.48)	(3.79)	1986	(1.47)
Spain	1.45***	(3.60)	(3.72)	1997	(2.30)
Sweden	1.52*	(1.94)	(23.03)***	2008***	(16.85)
Switzerland	0.82**	(2.14)	(0.00)	1991	(0.71)
United Kingdom	0.59	(1.24)	(0.44)	2000**	(3.38)
United States	0.56*	(1.66)	(0.43)	1996	(1.00)

(continued)

Table 2.7. (Continued)

Country	PY (2009a)		PSY (2017)		PY (2009b)	
	Annual trend (%)	<i>t-stat</i>	Wald stat	Break date	$W_{RQF}$	
Panel B: Comovements among emerging markets ( <i>PCA-emerging</i> )						
Argentina	-1.25	(-1.27)	(0.06)	2011***	(9.80)	
Brazil	-0.31	(-0.19)	(21.07)***	2005***	(29.93)	
Chile	0.98**	(2.36)	(5.17)*	2005	(1.23)	
China	1.99**	(2.38)	(5.95)*	2012*	(2.77)	
Colombia	2.09***	(3.73)	(2.21)	2005***	(23.13)	
Cyprus	1.00	(0.41)	(1.57)	2012***	(17.66)	
Czech Republic	0.15	(0.10)	(2.80)	2011**	(3.63)	
Greece	1.63	(0.55)	(1.96)	2012***	(18.75)	
Hungary	0.04	(0.05)	(1.61)	2012***	(43.19)	
India	0.90	(0.32)	(37.22)***	2007***	(34.14)	
Korea	1.08	(0.70)	(17.50)***	2012***	(9.75)	
Malaysia	0.33	(0.15)	(4.59)	2005***	(9.19)	
Mexico	0.25	(0.09)	(9.39)***	2005***	(35.78)	
Morocco	0.96**	(2.43)	(0.44)	2004***	(5.83)	
Pakistan	0.12	(0.59)	(3.03)	2004	(1.43)	
Peru	-0.13	(-0.11)	(0.93)	2006	(2.20)	
Philippine	1.08	(1.42)	(3.80)	2005***	(26.85)	
Poland	2.75	(1.08)	(1.77)	2012***	(39.80)	
South Africa	1.96**	(2.23)	(3.22)	2006***	(7.38)	
Sri Lanka	-0.51	(-1.10)	(0.10)	2009	(1.09)	
Thailand	0.38	(1.02)	(4.63)*	2015***	(8.51)	
Turkey	-0.09	(-0.03)	(20.35)***	2005***	(17.44)	
Venezuela	-0.52	(-0.65)	(0.86)	2011	(2.05)	
Panel C: Comovements between developing and developed markets ( <i>PCA</i> )						
Argentina	0.01	(0.01)	(0.06)	2003*	(2.97)	
Brazil	0.46	(0.15)	(3.53)	2005***	(39.47)	
Chile	1.94***	(4.53)	(2.74)	2005	(0.48)	
China	2.31**	(2.15)	(6.24)**	2006	(1.38)	
Colombia	0.90	(0.68)	(33.04)***	2005***	(6.09)	
Cyprus	0.18	(0.14)	(0.84)	2012**	(4.29)	
Czech Republic	1.58*	(1.81)	(14.77)***	2011***	(7.90)	
Greece	1.48	(0.61)	(23.28)***	2004***	(12.2)	
Hungary	1.53**	(1.98)	(5.72)*	2012***	(9.66)	
India	0.43	(0.24)	(46.46)***	2005*	(2.87)	
Korea	2.51*	(1.79)	(7.06)**	2012***	(23.75)	
Malaysia	-0.26	(-0.30)	(10.63)***	2005	(1.15)	
Mexico	0.66	(0.60)	(15.97)***	2009***	(7.09)	
Morocco	-0.59	(-0.56)	(0.66)	2012***	(5.43)	
Pakistan	0.48**	(2.05)	(1.85)	2012***	(8.50)	
Peru	0.93	(1.52)	(1.00)	2006	(2.11)	
Philippine	1.14*	(1.94)	(0.93)	2005	(1.05)	
Poland	2.44**	(2.24)	(9.94)***	2012***	(11.06)	
South Africa	0.91**	(2.11)	(0.25)	2005	(2.07)	
Sri Lanka	-0.31	(-1.12)	(0.62)	1998***	(5.90)	
Thailand	0.53	(1.54)	(0.60)	2013	(1.96)	
Turkey	0.70	(0.44)	(1.33)	2005***	(10.09)	
Venezuela	-0.41	(-1.12)	(1.43)	2015***	(93.68)	

*Notes:* This table presents the results of the linear deterministic trend test of Perron and Yabu, 2009a (PY). We report the annualized trends (%) and t-statistics (in parentheses). The 10%, 5%, and 1% critical values are 1.6, 2.0, and 2.6, respectively. Then, we use the non-linear deterministic trend test of Perron et al., 2017 (PSY), and set the frequency to one. The null hypothesis is that the non-linear components are not different than zero. The critical values for the Wald statistic are 4.6, 6.0, and 9.2 at 10%, 5%, and 1% significance levels, respectively. Finally, we control for structural breaks in the intercept and slope of the linear trend using the test of Perron and Yabu (2009b). The table reports the break dates and the test statistics ( $W_{RQF}$ ). The critical values for  $W_{RQF}$  are 2.7, 3.2, and 4.6 at 10% (\*), 5% (\*\*), and 1% (\*\*\*) significance levels, respectively. All tests are valid whether the errors are I(0) or I(1).

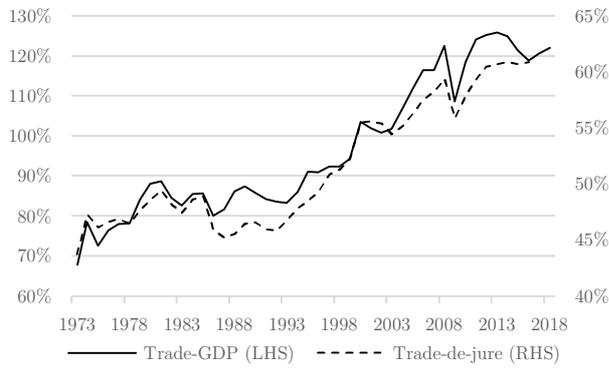


**Figure 2.1. Indicators of stock market comovements**

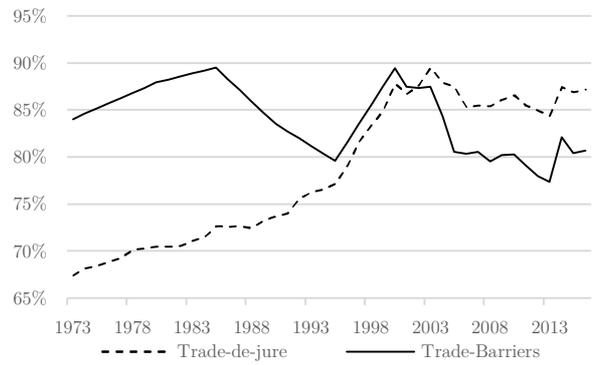
Based on several measures (see description in Section 2.4.b), this figure compares the evolution of comovements (i) among advanced markets, (ii) among emerging markets, and (iii) between developing and developed markets. For each annual observation, we compute the cross-sectional average between individuals. We report the results from 1993 and 1995 (for advanced and emerging markets, respectively), the first annual observations for which all data are available.

Appendix 2.2. Indicators of trade and financial openness

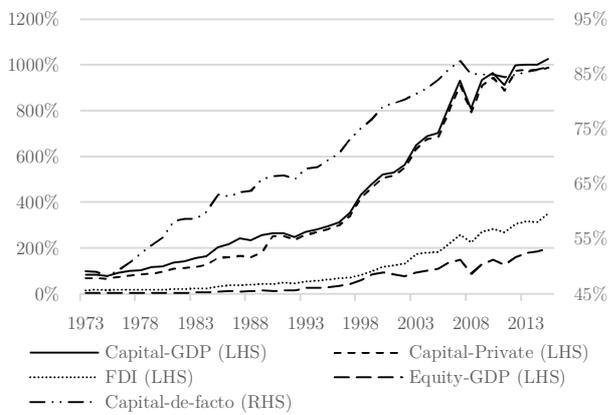
Panel 1: Trade openness - *de facto*



Panel 2: Trade openness - *de jure*



Panel 3: Financial openness - *de facto*



Panel 4: Financial openness - *de jure*

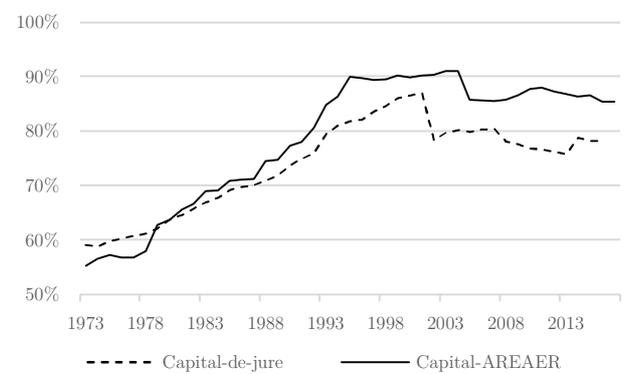
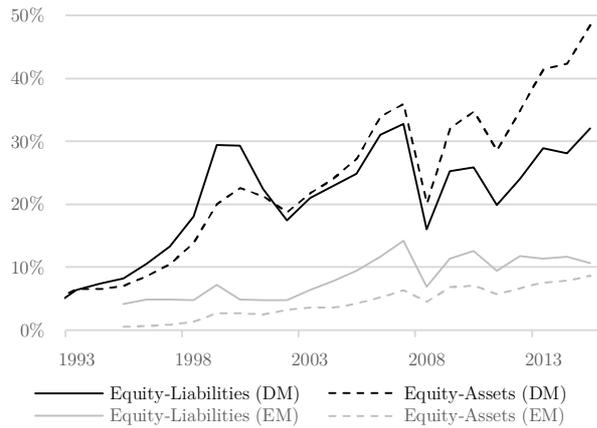
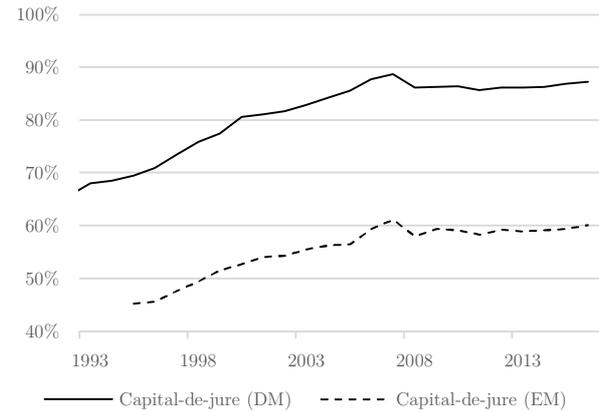


Figure 2.2. Trade and financial openness indicators

This figure describes the dynamics of the indicators of trade and financial openness over the period 1973–2018. All of the indicators are described in Table 2.2. For each annual observation, we compute the cross-sectional average for all individuals of the initial cohort.

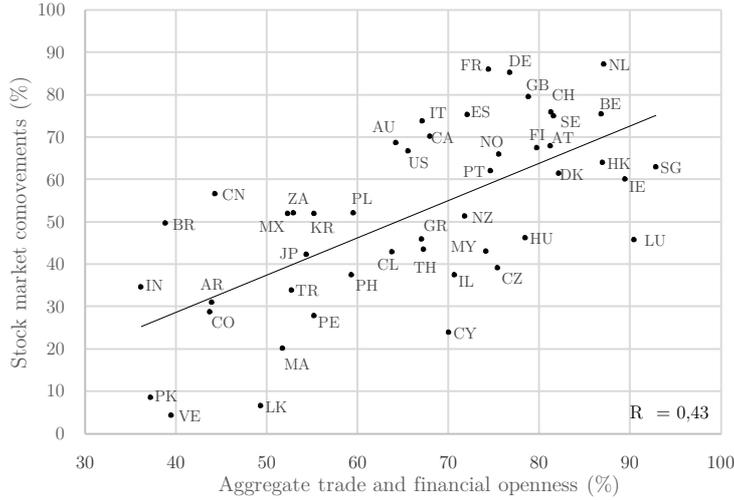
**Panel 1:** Equity asset and liabilities**Panel 2:** *De jure* financial openness**Figure 2.3. Equity holdings and *de jure* financial openness**

The first panel represents the evolutions of (i) the equity holdings for advanced and emerging markets. We exclude tax-havens from the cohort of advanced market economies. The second panel exhibits the dynamics of the *de jure* financial openness indicator (*Capital-de-jure*) of Gygli et al. (2019) for developed and emerging markets. *Abbreviations:* Advanced markets (DM); Emerging markets (EM)

### Appendix 2.3. Preliminary analysis

We perform preliminary investigations on the relationship between the degree of stock market comovements and the extent of trade and financial links between countries. The analysis relies on the main comovement indicator (*PCA*) and an aggregate trade and financial openness index (*Openness*) proposed by Gygli et al. (2019). This index is an equally weighted average of *Trade-de-facto*, *Trade-de-jure*, *Capital-de-facto*, and *Capital-de-jure* indicators.

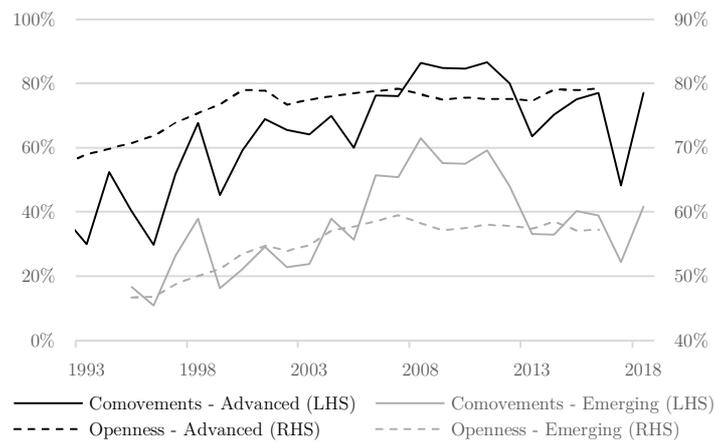
Based on a scatter plot (see Figure 2.4), we compare the average levels of the *PCA* and *Openness* indicators for each country. Our analysis reveals that European countries, such as France, Germany, and the Netherlands, display the highest level of comovements with the rest of the world. On the contrary, emerging markets, such as Pakistan, Sri Lanka, and Venezuela, are the least interdependent markets. Regarding the *Openness* indicator, we note that the most liberalized countries are tax-havens, such as Ireland, Luxembourg, and Singapore. By contrast, emerging market economies, such as Brazil, India, and Pakistan, remain less globalized. Overall, we observe that there is a positive relationship between *PCA* and *Openness*, with a coefficient of determination equal to 43.3%.



**Figure 2.4. Openness indicator vs. stock market comovements: cross-sectional analysis**

For each country, this figure compares the level of trade and financial openness (*Openness*) with the level of market comovements (*PCA*). The measures are based on average levels computed from 1995 to 2016, the longest period in which data are available for all countries.

Figure 2.5 illustrates the evolutions of the *PCA* and *Openness* indices. We divide our sample into two cohorts, the advanced markets (1993–2018) and the emerging markets (1995–2018). We first observe that *PCA* and *Openness* have increased on average over the past two decades for both advanced and emerging markets. The figure also suggests that there is a long-term cointegration relationship between the variables. We note that the *Openness* indicator seems to lead *PCA*, especially for developed markets.



**Figure 2.5. Openness indicator vs. stock market comovements: time-series analysis**

This figure compares the evolution of (i) the comovements (*PCA*) among advanced (solid black line) and emerging (solid grey line) markets and (ii) the openness indicators (*Openness*) for advanced (dashed black line) and emerging (dashed grey line) markets. For each annual observation, we compute the unweighted cross-sectional average of the *PCA* and *Openness* indicators. We report the results from 1993 and 1995 for advanced and emerging markets, respectively, which are the first annual observations in which all data are available.

**Table 2.8.** Descriptive statistics and diagnostic tests

Variables	Mean (%)	Median (%)	Standard Deviation (%)			Observations			Cross-Sectional Dependence Tests		Unit Root Tests				Westerlund Cointegration Test	
			Overall	Between	Within	N	n	T-bar	CD-stat	Correl	Level		First Differences		Gt stat	
											MW	CIPS	MW	CIPS		
<i>PCA</i>	48.3	50.6	27.6	17.3	22.0	1,638	47	34.8	89.5***	0.5	116.3*	-6.3***	773.5***	-15.9***	n/a	
Trade openness	<i>Trade-GDP</i>	86.2	62.8	73.7	66.7	24.3	1,634	47	34.7	77.3***	0.4	75.4	-0.5	460.0***	-5.4***	-2.3***
	<i>Trade-de-facto</i>	49.9	47.3	21.9	20.3	7.5	1,544	47	32.8	57.8***	0.3	89.3	0.7	418.3***	-6.4***	-2.2***
	<i>Exports</i>	43.9	31.1	39.0	35.4	13.2	1,634	47	34.7	72.9***	0.4	78.9	0.4	421.2***	-5.0***	-2.2***
	<i>Imports</i>	42.2	31.3	34.9	31.4	11.5	1,634	47	34.7	74.7***	0.4	66.5	-0.7	494.6***	-6.9***	-2.3***
	<i>Trade-Balance</i>	1.7	0.6	7.1	5.9	4.5	1,634	47	34.7	9.1***	0.05	112.9*	-0.2	444.7***	-8.7***	-1.7
	<i>Trade-de-jure</i>	77.7	80.9	13.2	11.9	7.0	1,543	47	32.9	36.9***	0.2	156.3***	-2.0**	280.4***	-9.1***	-1.7
Financial openness	<i>Capital-GDP</i>	608.1	158.5	2,608.1	2,683.2	1,193.7	1,491	47	31.7	101.4***	0.6	25.1	2.1	239.9***	-3.7***	-2.5***
	<i>FDI</i>	177.5	39.5	987.4	821.6	685.9	1,491	47	31.7	132.5***	0.8	18.2	8.8	274.7***	-8.4***	-2.3***
	<i>Capital-Private</i>	594.4	136.9	2,559.1	2,640.1	1,128.9	1,471	47	31.3	111.0***	0.6	27.9	0.5	251.2***	-5.0***	-2.2***
	<i>Capital-de-facto</i>	65.1	67.0	20.8	16.9	12.4	1,544	47	32.8	112.4***	0.7	172.7***	-1.3*	335.1***	-9.1***	-2.4***
	<i>Capital-Balance</i>	10.2	16.3	61.5	45.0	39.7	1,491	47	31.7	1.47	0.01	48.5	5.0	290.6***	-4.1***	-1.9**
	<i>Capital-AREAER</i>	34.8	23.1	31.6	27.4	17.8	1,565	46	34.0	n/a	n/a	113.0*	-1.1	341.0***	-10.8***	-1.9**
	<i>Capital-de-jure</i>	69.5	73.9	17.0	14.1	10.2	1,544	47	32.9	45.9***	0.2	135.5***	0.7	321.0***	-8.9***	-2.2***
	<i>Equity-GDP</i>	128.4	13.6	755.7	813.6	280.4	1,491	47	31.7	116.9***	0.7	23.7	0.2	389.1***	-4.8***	-2.4***
	<i>Equity-Liabilities</i>	83.9	7.4	528.8	571.5	176.0	1,491	47	31.7	96.5***	0.5	41.6	0.9	395.2***	-4.2***	-2.4***
	<i>Equity-Assets</i>	44.5	4.0	234.3	242.3	105.7	1,491	47	31.7	n/a	n/a	18.0	2.1	290.9***	-1.5*	-2.1***
<i>Equity-Balance</i>	39.4	1.6	295.9	329.8	79.9	1,491	47	31.7	7.2***	0.04	62.2	0.7	372.6***	-8.1***	-2.1***	

*Notes:* This table describes the main descriptive statistics and diagnostic tests of our panel dataset. We test for cross-sectional dependence (Pesaran, 2015). P-value close to zero indicates that data are correlated across panel groups. We also use the first- (Maddala and Wu, 1999 – MW) and second-generation (Pesaran, 2007 - CIPS) panel unit root tests, with two lags and without trend. The null hypothesis is that the series are I(1). Finally, we report the results of the bootstrap version of the panel cointegration test of Westerlund (2007). The null hypothesis is the absence of cointegration for the panel as a whole. The signs \*, \*\*, \*\*\* indicate significance at 10%, 5%, and 1% level, respectively.

## Appendix 2.4. Variables pre-selection

Table 2.9. Trade links—Univariate regressions (all countries)

	One lag		Two lags		Three lags		
	CS-ARDL	CS-DL	CS-ARDL	CS-DL	CS-ARDL	CS-DL	
Trade openness ( <i>de facto</i> )	<i>Trade-GDP</i>	0.573*** (0.194)	0.486*** (0.167)	0.430** (0.194)	0.406** (0.179)	0.550** (0.275)	0.415** (0.209)
	Observations	1,540	1,540	1,540	1,540	1,493	1,493
	ECT	-0.908***	n/a	-0.982***	n/a	-1.101***	n/a
	CD-test	-1.499	-0.877	-1.381	-1.257	-0.087	-0.673
	<i>Trade-de-facto</i>	0.574* (0.309)	0.615** (0.288)	0.429 (0.311)	0.464 (0.287)	0.085 (0.503)	0.452 (0.321)
	Observations	1,450	1,450	1,450	1,450	1,403	1,403
	ECT	-0.951***	n/a	-1.023***	n/a	-1.126***	n/a
	CD-test	-1.846*	-1.171	-0.930	-1.447	0.300	-1.334
	<i>Imports</i>	1.424*** (0.432)	1.294*** (0.377)	1.315** (0.520)	1.201*** (0.421)	-0.462 (2.188)	1.221*** (0.456)
	Observations	1,540	1,540	1,540	1,540	1,493	1,493
	ECT	-0.903***	n/a	-0.985***	n/a	-1.152***	n/a
	CD-test	-1.490	-0.621	-1.244	-0.968	-0.371	-0.578
	<i>Exports</i>	0.826*** (0.295)	0.688*** (0.261)	0.815** (0.397)	0.580** (0.251)	1.153* (0.595)	0.542* (0.280)
	Observations	1,540	1,540	1,540	1,540	1,493	1,493
	ECT	-0.921***	n/a	-0.989***	n/a	-1.091***	n/a
	CD-test	-1.483	-0.810	-0.930	-0.949	0.748	-0.328
<i>Trade-Balance</i>	1.083** (0.468)	0.654* (0.339)	1.104** (0.509)	0.656* (0.393)	1.387** (0.556)	0.721 (0.439)	
Observations	1,540	1,540	1,540	1,540	1,493	1,493	
ECT	-0.926***	n/a	-1.042***	n/a	-1.123***	n/a	
CD-test	-0.729	0.221	-0.328	0.223	0.127	0.435	
Trade openness ( <i>de jure</i> )	<i>Trade-Barriers</i>	0.543 (0.407)	0.169 (0.236)	0.714 (0.487)	0.148 (0.281)	0.117 (0.981)	0.189 (0.379)
	Observations	1,450	1,450	1,449	1,449	1,402	1,402
	ECT	-0.934***	n/a	-1.047***	n/a	-1.195***	n/a
	CD-test	-1.723*	-0.061	-1.265	0.271	-0.267	0.713
	<i>Trade-de-jure</i>	0.805*** (0.199)	0.887*** (0.161)	0.693*** (0.200)	0.908*** (0.173)	0.941*** (0.213)	1.062*** (0.215)
	Observations	1,450	1,450	1,450	1,450	1,403	1,403
	ECT	-0.904***	n/a	-1.004***	n/a	-1.148***	n/a
	CD-test	-2.069**	-0.812	-1.699*	-0.749	-0.950	-0.594

*Notes:* This table analyzes the long-term impact of trade openness on market interdependencies. The dependent variable is our baseline measure of comovements (*PCA*). The results are based on the CS-ARDL and CS-DL models with one, two, and three lags of the variables. To handle potential omitted factor bias, we also include the contemporaneous values and two lags of the CSA of the variables. Standard errors are in parentheses. The signs \*, \*\*, and \*\*\* indicate significance at the 10, 5, and 1% level, respectively.

**Table 2.10.** Financial links—Univariate regressions (all countries)

		One lag		Two lags		Three lags	
		CS-ARDL	CS-DL	CS-ARDL	CS-DL	CS-ARDL	CS-DL
Financial openness ( <i>de facto</i> )	<i>Capital-GDP</i>	-0.026 (0.056)	0.009 (0.049)	-0.072 (0.076)	-0.012 (0.054)	0.155 (0.243)	0.050 (0.072)
	Observations	1,398	1,398	1,397	1,397	1,350	1,350
	ECT	-0.960***	n/a	-1.060***	n/a	-1.193***	n/a
	CD-test	-1.519	-0.577	-1.048	-0.585	-0.726	-0.610
	<i>Capital-de-facto</i>	0.257 (0.188)	0.323* (0.194)	0.201 (0.206)	0.308 (0.212)	0.413 (0.344)	0.474* (0.261)
	Observations	1,450	1,450	1,450	1,450	1,403	1,403
	ECT	-0.968***	n/a	-1.056***	n/a	-1.216***	n/a
	CD-test	-2.266**	-2.434**	-1.045	-1.941*	0.340	-1.640
	<i>FDI</i>	0.043 (0.224)	0.231 (0.173)	-0.149 (0.317)	0.160 (0.199)	-0.186 (0.400)	0.072 (0.243)
	Observations	1,398	1,398	1,397	1,397	1,350	1,350
	ECT	-0.961***	n/a	-1.048***	n/a	-1.183***	n/a
	CD-test	-1.252	-0.623	-1.022	-0.668	-0.524	-0.494
	<i>Capital-Private</i>	-0.057 (0.055)	-0.027 (0.047)	-0.127 (0.122)	-0.068 (0.072)	-0.006 (0.081)	-0.079 (0.084)
	Observations	1,377	1,377	1,374	1,374	1,326	1,326
	ECT	-0.948***	n/a	-1.048***	n/a	-1.242***	n/a
	CD-test	-2.294**	-1.986*	-1.813*	-1.873*	-0.881	-1.713*
<i>Capital-Balance</i>	-0.088 (0.089)	-0.067 (0.068)	-0.104 (0.137)	-0.067 (0.074)	0.218 (0.231)	0.005 (0.074)	
Observations	1,398	1,398	1,397	1,397	1,350	1,350	
ECT	-0.907***	n/a	-1.025***	n/a	-1.181***	n/a	
CD-test	-0.950	-0.143	-0.408	-0.408	0.792	-0.175	
Financial openness ( <i>de jure</i> )	<i>Capital-AREAER</i>	0.354*** (0.119)	0.305*** (0.113)	0.344** (0.140)	0.340*** (0.128)	0.449** (0.189)	0.344** (0.161)
	Observations	1,473	1,473	1,473	1,473	1,427	1,427
	ECT	-0.899***	n/a	-1.028***	n/a	-1.184***	n/a
	CD-test	-2.460**	-1.604	-2.077**	-1.461	-1.268	-0.738
	<i>Capital-de-jure</i>	0.357** (0.167)	0.370** (0.167)	0.381* (0.219)	0.458** (0.187)	0.624*** (0.213)	0.539*** (0.198)
	Observations	1,450	1,450	1,450	1,450	1,403	1,403
ECT	-0.909***	n/a	-0.990***	n/a	-1.132***	n/a	
CD-test	-1.466	-0.802	-1.244	-0.832	-1.012	-1.238	
Equity market openness ( <i>de facto</i> )	<i>Equity-GDP</i>	1.431*** (0.377)	1.275*** (0.261)	1.873* (1.001)	1.081*** (0.267)	-2.035 (2.936)	1.197*** (0.282)
	Observations	1,398	1,398	1,397	1,397	1,350	1,350
	ECT	-0.945***	n/a	-1.057***	n/a	-1.180***	n/a
	CD-test	-0.588	0.013	-0.594	-0.250	0.192	-0.290
	<i>Equity-Liabilities</i>	1.484*** (0.454)	1.543*** (0.417)	1.396*** (0.521)	1.368*** (0.451)	2.134** (0.944)	1.228*** (0.385)
	Observations	1,398	1,398	1,397	1,397	1,350	1,350
	ECT	-0.942***	n/a	-1.065***	n/a	-1.198***	n/a
	CD-test	-0.259	0.490	-0.065	0.038	0.861	0.409
	<i>Equity-Assets</i>	-4.011 (2.747)	-3.343 (3.300)	-4.260 (2.955)	-4.099 (3.648)	-5.932 (4.276)	-1.952 (1.464)
	Observations	1,398	1,398	1,397	1,397	1,350	1,350
	ECT	-0.932***	n/a	-1.044***	n/a	-1.124***	n/a
	CD-test	-0.972	-0.547	-0.141	-0.383	0.354	-0.323
<i>Equity-Balance</i>	0.741*** (0.281)	0.757** (0.342)	0.855** (0.354)	0.568* (0.320)	1.978 (5.067)	0.457 (0.439)	
Observations	1,398	1,398	1,397	1,397	1,350	1,350	
ECT	-0.939***	n/a	-1.023***	n/a	-1.100***	n/a	
CD-test	-0.850	-0.566	-0.674	-0.883	-0.755	-0.834	

*Notes:* This table examines the long-term impact of financial openness on market interdependencies. The dependent variable is our baseline measure of comovements (*PCA*). The results are based on the CS-ARDL and CS-DL models with one, two, and three lags of the variables. To handle potential omitted factor bias, we also include the contemporaneous values and two lags of the CSA of the variables. Standard errors are in parentheses. The signs \*, \*\*, and \*\*\* indicate significance at the 10, 5, and 1% level, respectively.

## Appendix 2.5. Alternative dependent variables

Table 2.11. Alternative dependent variables—Univariate regressions (all countries)

	<i>PCA</i>	<i>PCA-local-currency</i>	<i>PCA-local-sector</i>	<i>PCA-all-markets</i>	<i>ICAPM-R<sup>2</sup></i>	<i>ICAPM-beta</i>	<i>Correlation</i>
Trade-GDP	0.406** (0.179)	0.466** (0.187)	0.239 (0.170)	0.420*** (0.158)	0.358** (0.159)	0.410 (0.393)	0.391** (0.155)
Observations	1,540	1,540	1,540	1,540	1,540	1,540	1,540
CD-test	-1.257	-0.680	-0.886	-1.591	-1.893	-1.243	0.704
Trade-de-jure	0.908*** (0.173)	0.800*** (0.213)	0.624*** (0.126)	0.901*** (0.163)	0.560*** (0.176)	0.140 (0.451)	0.525*** (0.120)
Observations	1,450	1,450	1,450	1,450	1,450	1,450	1,450
CD-test	-0.749	0.012	-1.152	-1.229	-1.566	-1.195	0.074
Equity-Liabilities	1.368*** (0.451)	0.842** (0.411)	0.941*** (0.345)	1.490*** (0.510)	1.368*** (0.365)	1.434* (0.839)	0.860** (0.436)
Observations	1,397	1,397	1,397	1,397	1,397	1,397	1,397
CD-test	0.038	0.400	-0.176	-0.497	-0.806	-1.616	2.471**
Capital-GDP	-0.012 (0.054)	-0.102 (0.067)	-0.026 (0.058)	-0.065 (0.056)	-0.086* (0.050)	0.032 (0.117)	-0.048 (0.042)
Observations	1,397	1,397	1,397	1,397	1,397	1,397	1,397
CD-test	-0.585	0.509	-0.490	-1.088	-1.459	-1.018	1.758*
Capital-de-jure	0.458** (0.187)	0.665*** (0.203)	0.353*** (0.121)	0.410** (0.189)	0.383** (0.149)	0.649** (0.254)	0.389*** (0.114)
Observations	1,450	1,450	1,450	1,450	1,450	1,450	1,450
CD-test	-0.832	-0.272	-0.213	-0.904	-1.212	-0.965	0.863

*Notes:* This table controls the robustness of our results to alternative dependent variables. We use six alternative indicators of stock market comovements described in Section 2.4.b: *PCA-local-currency*, *PCA-local-sectors*, *PCA-all-markets*, *ICAPM-R<sup>2</sup>*, *ICAPM-beta*, and *Correlation*. Estimates are based on the CS-DL model with two lags of the independent variables. To handle potential omitted factor bias, we also include the contemporaneous values and two lags of the CSA of the variables. Standard errors are in parentheses. The signs \*, \*\*, and \*\*\* indicate significance at the 10, 5, and 1% level, respectively.

**Table 2.12.** Alternative dependent variables—Multivariate regressions

Panel A: Comovements among advanced markets									
	<i>PCA-local-currency</i>			<i>PCA-local-sector</i>			<i>PCA-all-markets</i>		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Trade-GDP	0.933*** (0.275)	0.751*** (0.279)	0.695** (0.345)	0.378** (0.153)	0.469 (0.321)	0.498 (0.390)	0.642*** (0.212)	0.596* (0.318)	0.478 (0.313)
Trade-de-jure	0.892*** (0.343)	1.459** (0.687)	1.313* (0.725)	0.567*** (0.166)	0.810** (0.324)	0.487 (0.636)	0.704*** (0.231)	1.028* (0.547)	1.028* (0.568)
Equity-Liabilities		0.169 (0.143)	-0.802 (0.523)		-0.110 (0.151)	-1.569** (0.675)		0.011 (0.155)	-0.893* (0.535)
Capital-de-jure		-0.474 (0.372)	-0.569 (0.394)		-0.226 (0.199)	-0.173 (0.527)		-0.294 (0.304)	-0.348 (0.499)
MktCap-GDP			0.420** (0.189)			0.768** (0.383)			0.262 (0.214)
CD-test	-0.440	-0.871	-1.817*	0.462	-0.618	-0.324	0.323	-0.672	-1.396
	<i>ICAPM-R<sup>2</sup></i>			<i>ICAPM-beta</i>			<i>Correlation</i>		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Trade-GDP	0.436** (0.200)	0.319 (0.197)	0.126 (0.242)	1.210*** (0.394)	1.596*** (0.495)	1.283*** (0.448)	0.395*** (0.134)	0.286** (0.140)	0.207 (0.151)
Trade-de-jure	0.607** (0.255)	0.846 (0.690)	0.912 (0.664)	-0.713 (0.448)	-0.948 (1.189)	-0.351 (1.206)	0.443*** (0.149)	0.375 (0.414)	0.321 (0.326)
Equity-Liabilities		0.074 (0.199)	-0.577 (0.560)		-0.583* (0.309)	-1.844* (1.110)		-0.040 (0.125)	-0.805** (0.323)
Capital-de-jure		-0.563 (0.365)	-0.684 (0.423)		-0.854 (0.625)	-1.031 (0.695)		-0.153 (0.154)	-0.077 (0.242)
MktCap-GDP			0.336 (0.204)			0.475 (0.479)			0.369** (0.151)
CD-test	0.572	-0.314	-0.844	5.394***	2.788***	3.098***	3.596***	2.320**	1.710*
Panel B: Comovements among emerging markets									
	<i>PCA-local-currency</i>			<i>PCA-local-sector</i>			<i>PCA-all-markets</i>		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Trade-GDP		-0.160 (0.401)	-0.123 (0.607)		-0.366 (0.252)	0.006 (0.365)		n/a	n/a
Trade-de-jure		-0.295 (0.684)	0.185 (0.873)		0.264 (0.390)	-0.152 (0.599)		n/a	n/a
Equity-Liabilities	1.534** (0.694)	3.496** (1.486)	5.235** (2.299)	2.093*** (0.566)	2.175** (1.095)	2.166 (2.081)	n/a	n/a	n/a
Capital-de-jure	0.189 (0.189)	0.258 (0.431)	0.479 (0.618)	0.007 (0.137)	-0.468 (0.312)	-0.917** (0.358)	n/a	n/a	n/a
MktCap-GDP			-1.513** (0.723)			-0.213 (0.402)			n/a
CD-test	2.224**	4.262***	1.133	1.243	0.079	-0.044	n/a	n/a	n/a
	<i>ICAPM-R<sup>2</sup></i>			<i>ICAPM-beta</i>			<i>Correlation</i>		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Trade-GDP		-0.326 (0.345)	-0.413 (0.660)		0.121 (0.801)	0.427 (1.099)		-0.154 (0.180)	0.099 (0.315)
Trade-de-jure		0.141 (0.455)	-0.122 (0.624)		-0.085 (1.044)	3.045** (1.513)		0.166 (0.244)	-0.434 (0.451)
Equity-Liabilities	2.775*** (0.714)	3.174*** (0.931)	5.644** (2.380)	2.204 (1.487)	2.771 (1.940)	1.036 (5.409)	1.591*** (0.536)	0.811** (0.396)	1.403 (1.488)
Capital-de-jure	0.271 (0.201)	0.414 (0.376)	0.046 (0.564)	0.658** (0.322)	1.060 (0.788)	-0.273 (1.042)	0.069 (0.123)	0.058 (0.168)	-0.258 (0.362)
MktCap-GDP			-1.108** (0.547)			-1.495 (1.491)			-0.568** (0.236)
CD-test	0.348	1.277	0.634	-1.246	-0.763	-0.919	8.772***	5.788***	2.088**

(continued)

Table 2.12. (Continued)

Panel C: Comovements between developing and developed markets									
	<i>PCA-local-currency</i>			<i>PCA-local-sector</i>			<i>PCA-all-markets</i>		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Trade-GDP		-0.264 (0.398)	0.093 (0.506)		-0.277* (0.165)	0.057 (0.292)		0.025 (0.285)	0.345 (0.405)
Trade-de-jure		0.035 (0.609)	-1.532 (0.964)		0.527 (0.334)	-0.128 (0.393)		0.024 (0.559)	0.017 (0.658)
Equity-Liabilities	1.241** (0.591)	2.050** (0.936)	8.562*** (2.901)	1.527** (0.708)	2.118*** (0.784)	2.562 (1.743)	2.210*** (0.718)	1.419 (0.911)	4.601** (1.769)
Capital-de-jure	0.545*** (0.190)	0.932*** (0.359)	0.618 (0.512)	0.160 (0.154)	-0.313 (0.332)	-0.193 (0.357)	0.243 (0.173)	0.542 (0.394)	0.934* (0.564)
MktCap-GDP			-2.171 (1.558)			-0.415 (0.314)			-1.176 (0.715)
CD-test	-1.082	-0.485	-0.948	-0.599	-0.332	-1.068	-1.618	-1.113	-1.558
	<i>ICAPM-R<sup>2</sup></i>			<i>ICAPM-beta</i>			<i>Correlation</i>		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Trade-GDP		-0.100 (0.303)	0.353 (0.459)		0.927 (0.753)	1.887** (0.926)		0.042 (0.233)	0.569 (0.545)
Trade-de-jure		0.095 (0.405)	-0.161 (0.365)		-0.178 (0.786)	1.502 (0.973)		0.382 (0.326)	-0.194 (0.470)
Equity-Liabilities	2.216*** (0.625)	1.504* (0.886)	3.955** (1.825)	3.642* (1.881)	1.338 (1.865)	10.36 (6.787)	1.425** (0.687)	-0.047 (0.674)	2.308 (2.122)
Capital-de-jure	0.313** (0.131)	0.238 (0.241)	-0.045 (0.406)	0.839** (0.390)	0.768 (0.776)	0.644 (1.250)	0.390*** (0.110)	0.271 (0.182)	0.254 (0.451)
MktCap-GDP			-0.533 (0.341)			-2.259** (0.965)			-0.983** (0.397)
CD-test	0.145	0.467	-0.698	-0.267	0.385	-0.133	0.048	0.494	1.104

*Notes:* This table controls the robustness of our findings to alternative dependent variables. We report separate results for the comovements (i) among advanced markets (Panel A), (ii) among emerging markets (Panel B), and (iii) between developing and developed markets (Panel C). We use six alternative indicators of stock market comovements described in Section 2.4.b. For each alternative measure, Specification 1 tests the two most likely regressors, as defined in Section 2.5. Specification 2 includes all regressors, and Specification 3 adds the control variable (*MktCap-GDP*). Estimates are based on the CS-DL model with one lag of the independent variables, augmented with contemporaneous values of the CSA. Standard errors are in parentheses. The signs \*, \*\*, and \*\*\* indicate significance at the 10, 5, and 1% level, respectively.

## Appendix 2.6. Alternative estimators

Table 2.13. MG estimator with outlier-robust averages of the individual estimates

<i>Panel A: Comovements among advanced markets</i>											
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Trade-GDP		0.383 (0.247)		0.613*** (0.159)		0.609** (0.252)		0.390 (0.251)	0.280 (0.223)	0.548* (0.322)	0.610* (0.315)
Trade-de-jure	0.713** (0.324)			0.675** (0.272)	0.586 (0.368)		0.681 (0.444)	0.344 (0.327)	1.147*** (0.441)		0.930** (0.404)
Equity-Liabilities		-0.165 (0.212)	-0.081 (0.251)		0.294 (0.334)		0.261 (0.392)	0.205 (0.323)		-0.206 (0.328)	-0.285 (0.274)
Capital-de-jure	0.154 (0.357)		0.181 (0.257)			0.234 (0.243)	-0.055 (0.311)		-0.387 (0.336)	-0.086 (0.271)	-0.533 (0.383)
MktCap-GDP		0.369*** (0.127)	0.248* (0.129)		0.094 (0.175)		0.111 (0.190)	0.160 (0.152)		0.432*** (0.159)	0.199 (0.162)
CD-test	-0.250	-0.173	1.215	-0.632	-0.647	1.222	-0.447	-1.385	-0.876	-0.306	-1.426
<i>Panel B: Comovements among emerging markets</i>											
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Trade-GDP		0.003 (0.243)		-0.030 (0.199)		-0.143 (0.206)		0.236 (0.334)	-0.262 (0.229)	-0.151 (0.353)	-0.532 (0.515)
Trade-de-jure	0.546* (0.326)			0.277 (0.241)	0.241 (0.302)		0.282 (0.581)	-0.170 (0.505)	0.466 (0.558)		-0.083 (0.850)
Equity-Liabilities		3.012*** (1.057)	2.374*** (0.898)		3.708*** (1.378)		3.244** (1.366)	2.514 (1.776)		2.541 (1.672)	7.198*** (2.533)
Capital-de-jure	0.168 (0.271)		-0.025 (0.264)			0.314 (0.217)	-0.405 (0.390)		0.070 (0.331)	-0.082 (0.350)	-0.331 (0.531)
MktCap-GDP		-0.227 (0.308)	-0.182 (0.194)		-0.046 (0.210)		-0.415 (0.357)	-0.078 (0.335)		-0.124 (0.392)	-0.814 (0.576)
CD-test	0.534	1.754*	-0.515	3.024***	1.467	0.718	-0.087	1.698*	1.344	-0.073	3.671***
<i>Panel C: Comovements between developing and developed markets</i>											
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Trade-GDP		-0.076 (0.252)		0.097 (0.181)		0.086 (0.141)		0.026 (0.258)	-0.042 (0.195)	-0.042 (0.218)	0.325 (0.277)
Trade-de-jure	0.527* (0.295)			0.561*** (0.192)	0.130 (0.249)		0.314 (0.462)	-0.156 (0.202)	0.507** (0.250)		-0.198 (0.575)
Equity-Liabilities		2.345** (1.165)	2.078* (1.189)		2.476** (1.179)		1.003 (0.721)	2.959* (1.599)		1.021 (0.829)	4.583** (1.915)
Capital-de-jure	0.346* (0.204)		0.093 (0.188)			0.428*** (0.153)	-0.218 (0.322)		0.246 (0.224)	0.182 (0.333)	0.012 (0.531)
MktCap-GDP		-0.117 (0.160)	0.111 (0.149)		-0.139 (0.195)		0.115 (0.088)	-0.116 (0.224)		-0.029 (0.230)	-0.328 (0.448)
CD-test	-1.393	-1.262	-1.272	-1.132	-0.323	-1.448	-0.959	-0.375	-1.102	-1.339	-1.116

*Notes:* This table controls the robustness of our main results using outlier-robust averages of the individual coefficients. All estimations are based on the CS-DL model with one lag of the independent variables, augmented with contemporaneous values of the CSA. We do not include additional lags due to the limited time dimension of our dataset. Standard errors are in parentheses. The signs \*, \*\*, and \*\*\* indicate significance at the 10, 5, and 1% level, respectively.

**Table 2.14.** Pooled mean group (PMG) and dynamic fixed effects (DFE) estimators

Comovements among emerging markets											
<i>CS-ARDL – PMG estimator</i>											
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Trade-GDP		-0.403** (0.063)		-0.334** (0.059)		-0.323** (0.091)		-0.276** (0.067)	-0.345** (0.079)	-0.285** (0.070)	-0.044 (0.064)
Trade-de-jure	-0.248** (0.126)			0.197* (0.118)	0.014 (0.098)		0.172 (0.109)	0.174* (0.097)	0.160 (0.134)		0.099 (0.083)
Equity-Liabilities		1.418*** (0.184)	1.079*** (0.230)		0.990*** (0.216)		0.760*** (0.215)	1.111*** (0.191)		1.264*** (0.148)	0.639*** (0.111)
Capital-de-jure	0.032 (0.098)		0.165** (0.079)			0.145 (0.091)	-0.091 (0.086)		0.029 (0.083)	0.290*** (0.068)	0.110 (0.073)
MktCap-GDP		0.031 (0.041)	0.004 (0.058)		-0.093** (0.045)		-0.071 (0.050)	-0.007 (0.041)		0.112*** (0.036)	0.081*** (0.024)
N	502	478	479	500	479	500	479	478	500	478	478
n	23	23	23	23	23	23	23	23	23	23	23
Tbar	21.83	20.79	20.83	21.75	20.83	21.75	20.83	20.79	21.75	20.79	20.79
ECT	-1.03***	-1.09***	-1.08***	-1.08***	-1.13***	-1.02***	-1.16***	-1.16***	-1.09***	-1.12***	-1.25***
CD-test	2.546**	4.206***	3.871***	4.304***	3.899***	4.773***	2.021**	4.194***	2.371**	3.033***	2.665***
<i>CS-ARDL – DFE estimator</i>											
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Trade-GDP		-0.043 (0.062)		-0.032 (0.067)		-0.094 (0.064)		-0.033 (0.062)	-0.090 (0.063)	-0.072 (0.060)	-0.074 (0.059)
Trade-de-jure	-0.133 (0.127)			0.155 (0.120)	0.016 (0.110)		-0.249** (0.118)	0.021 (0.111)	-0.197 (0.128)		-0.261** (0.119)
Equity-Liabilities		1.357*** (0.235)	1.060*** (0.234)		1.270*** (0.241)		1.066*** (0.232)	1.288*** (0.242)		1.086*** (0.233)	1.074*** (0.232)
Capital-de-jure	0.501*** (0.093)		0.314*** (0.079)			0.459*** (0.084)	0.424*** (0.088)		0.546*** (0.095)	0.333*** (0.080)	0.448*** (0.089)
MktCap-GDP		0.073 (0.065)	0.065 (0.062)		0.053 (0.063)		0.059 (0.060)	0.057 (0.064)		0.077 (0.062)	0.060 (0.061)
N	502	478	479	500	479	500	479	478	500	478	478
n	23	23	23	23	23	23	23	23	23	23	23
Tbar	21.83	20.79	20.83	21.75	20.83	21.75	20.83	20.79	21.75	20.79	20.79
ECT	-0.84***	-0.89***	-0.91***	-0.80***	-0.89***	-0.83***	-0.92***	-0.89***	-0.85***	-0.92***	-0.92***
CD-test	2.490**	1.919*	2.851***	2.545**	1.052	4.518***	0.826	0.963	1.777*	2.307**	0.738

*Notes:* This table controls the robustness of our results to various estimation methods (i.e., pooled mean group and dynamic fixed effects). All estimations are based on the CS-ARDL model with one lag of the variables, augmented with contemporaneous values of the CSA. Standard errors are in parentheses. The signs \*, \*\*, and \*\*\* indicate significance at the 10, 5, and 1% level, respectively.

## Appendix 2.7. Univariate regressions for advanced and emerging markets

Table 2.15. Trade links—Univariate regressions (CS-DL)—Details by groups

	Advanced countries			Emerging countries			Emerging vs. advanced countries			
	One lag	Two lags	Three lags	One lag	Two lags	Three lags	One lag	Two lags	Three lags	
Trade openness ( <i>de facto</i> )	<i>Trade-GDP</i>	0.913*** (0.253)	0.861*** (0.271)	0.864*** (0.299)	0.057 (0.270)	0.030 (0.307)	0.095 (0.520)	0.040 (0.178)	-0.069 (0.192)	-0.054 (0.263)
	Observations	938	938	914	521	521	498	602	602	579
	CD-test	2.126**	1.462	1.642	4.313***	4.461***	3.789***	-0.371	-0.918	-0.358
	<i>Trade-de-facto</i>	1.236*** (0.446)	1.010** (0.459)	0.911* (0.524)	-0.198 (0.476)	-0.108 (0.516)	0.017 (0.570)	-0.032 (0.317)	-0.105 (0.305)	-0.026 (0.347)
	Observations	890	890	866	479	479	456	560	560	537
	CD-test	1.979**	1.183	0.736	2.593***	2.551**	1.531	-0.954	-1.525	-1.547
	<i>Imports</i>	2.285*** (0.585)	2.277*** (0.634)	2.388*** (0.690)	0.474 (0.465)	0.664 (0.502)	0.496 (0.644)	0.259 (0.370)	0.079 (0.453)	0.003 (0.489)
	Observations	938	938	914	521	521	498	602	602	579
	CD-test	2.759***	2.539**	2.896***	4.731***	4.752***	3.988***	0.192	-0.727	-0.603
	<i>Exports</i>	1.433*** (0.395)	1.317*** (0.404)	1.276*** (0.437)	-0.519 (0.383)	-0.844* (0.493)	-0.796 (0.555)	-0.089 (0.256)	-0.190 (0.194)	-0.223 (0.275)
	Observations	938	938	914	521	521	498	602	602	579
	CD-test	2.667***	1.972**	2.397**	3.751***	3.417***	3.357***	-0.403	-0.622	-0.250
<i>Trade-Balance</i>	1.343*** (0.507)	1.393** (0.581)	1.666** (0.655)	-0.359 (0.382)	-0.154 (0.599)	0.122 (0.732)	0.205 (0.476)	0.544 (0.780)	0.442 (0.802)	
Observations	938	938	914	521	521	498	536	521	498	
CD-test	4.739***	5.152***	5.021***	2.826***	2.558**	1.839*	-1.307	-1.420	-0.608	
Trade openness ( <i>de jure</i> )	<i>Trade-Barriers</i>	0.048 (0.032)	0.042 (0.038)	0.021 (0.038)	0.008 (0.042)	0.013 (0.045)	0.054 (0.071)	-0.016 (0.034)	-0.014 (0.041)	0.017 (0.068)
	Observations	890	890	866	479	478	455	560	559	536
	CD-test	4.319***	4.685***	4.494***	2.364**	2.191**	1.386	-1.507	-1.450	-1.395
	<i>Trade-de-jure</i>	1.120*** (0.270)	1.133*** (0.284)	1.209*** (0.327)	0.620** (0.243)	0.732** (0.291)	0.996*** (0.378)	0.643*** (0.161)	0.672*** (0.187)	0.908*** (0.282)
	Observations	890	890	866	479	479	456	560	560	537
	CD-test	1.310	1.214	1.470	3.608***	3.796***	3.696***	0.150	0.174	-0.513

*Notes:* This table analyzes the long-term impact of trade openness on market interdependencies. We report separate results for the comovements (i) among advanced markets, (ii) among emerging markets, and (iii) between developing and developed markets. The dependent variables are our baseline measures of comovements (*PCA* and *PCA-emerging*). The results are based on the CS-DL model with two lags of the variables and the CSA. Standard errors are in parentheses. The signs \*, \*\*, and \*\*\* indicate significance at the 10, 5, and 1% level, respectively.

**Table 2.16.** Financial links—Univariate regressions (CS-DL)—Details by groups

	Advanced countries			Emerging countries			Emerging vs. advanced countries			
	One lag	Two lags	Three lags	One lag	Two lags	Three lags	One lag	Two lags	Three lags	
Financial openness ( <i>de facto</i> )	<i>Capital-GDP</i>	0.068** (0.029)	0.069** (0.032)	0.065** (0.032)	-0.107 (0.094)	-0.244** (0.122)	-0.316* (0.161)	-0.053 (0.094)	-0.097 (0.103)	0.035 (0.144)
	Observations	861	860	836	456	456	433	537	537	514
	CD-test	3.068***	2.980***	3.272***	4.021***	2.535**	2.120**	-0.817	-0.956	-0.924
	<i>Capital-de-facto</i>	0.850*** (0.199)	0.771*** (0.214)	0.943*** (0.265)	-0.028 (0.330)	0.109 (0.451)	0.025 (0.505)	-0.228 (0.301)	-0.175 (0.347)	-0.016 (0.439)
	Observations	890	890	866	479	479	456	560	560	537
	CD-test	1.772*	2.969***	3.541***	3.386***	2.907***	2.311**	-0.723	-1.091	-0.630
	<i>FDI</i>	0.284*** (0.100)	0.227** (0.112)	0.195 (0.130)	0.604 (0.375)	0.325 (0.266)	-0.118 (0.326)	0.302 (0.271)	0.220 (0.285)	0.164 (0.346)
	Observations	933	932	908	521	521	498	602	602	579
	CD-test	3.736***	3.346***	3.667***	5.124***	4.795***	4.264***	-0.263	-0.110	-0.219
	<i>Capital-Private</i>	0.073** (0.029)	0.074** (0.033)	0.037 (0.024)	-0.125 (0.120)	-0.186 (0.203)	0.015 (0.289)	-0.262* (0.139)	-0.363* (0.199)	-0.440 (0.279)
	Observations	844	842	818	454	454	431	535	535	512
	CD-test	1.788*	2.249**	-3.070***	4.212***	3.213***	-2.503**	-0.960	-1.091	-2.653***
	<i>Capital-Balance</i>	-0.082 (0.092)	-0.072 (0.087)	-0.090 (0.084)	0.133* (0.068)	0.159 (0.098)	0.211 (0.136)	0.223** (0.092)	0.212* (0.116)	0.104 (0.123)
	Observations	861	860	836	456	456	433	537	537	514
	CD-test	4.319***	4.057***	3.450***	4.850***	4.809***	1.447	-0.607	-0.703	-0.687
Financial openness ( <i>de jure</i> )	<i>Capital-AREAER</i>	0.295* (0.177)	0.307* (0.185)	0.257 (0.242)	0.181 (0.196)	0.136 (0.236)	0.049 (0.250)	0.310** (0.128)	0.364** (0.170)	0.420** (0.195)
	Observations	890	890	867	502	502	479	583	583	560
	CD-test	2.233**	2.747***	3.218***	1.109	1.861*	1.211	-0.173	0.210	0.276
	<i>Capital-de-jure</i>	0.283 (0.296)	0.455 (0.335)	0.533 (0.359)	0.242 (0.166)	0.218 (0.184)	0.209 (0.176)	0.460*** (0.152)	0.462*** (0.163)	0.545*** (0.166)
	Observations	890	890	866	479	479	456	560	560	537
	CD-test	3.505***	3.880***	3.287***	2.016**	1.174	-0.033	0.481	0.772	-0.059

*Notes:* This table examines the long-term impact of financial openness on market interdependencies. We report separate results for the comovements (i) among advanced markets, (ii) among emerging markets, and (iii) between developing and developed markets. The dependent variables are our baseline measures of comovements (*PCA* and *PCA-emerging*). The results are based on the CS-DL model with two lags of the variables and the CSA. Standard errors are in parentheses. The signs \*, \*\*, and \*\*\* indicate significance at the 10, 5, and 1% level, respectively.

**Table 2.17.** Equity openness—Univariate regressions (CS-DL)—Details by groups

	Advanced countries			Emerging countries			Emerging vs. advanced countries			
	One lag	Two lags	Three lags	One lag	Two lags	Three lags	One lag	Two lags	Three lags	
Equity market openness ( <i>de facto</i> )	<i>Equity-GDP</i>	0.511*** (0.131)	0.503*** (0.145)	0.559*** (0.154)	2.075*** (0.557)	2.336*** (0.597)	2.684*** (0.596)	2.073*** (0.464)	1.685*** (0.498)	1.863*** (0.524)
	Observations	861	860	836	456	456	433	537	537	514
	CD-test	3.707***	3.383***	3.347***	2.214**	2.504**	0.765	-1.477	-1.642	-1.538
	<i>Equity-Liabilities</i>	0.527*** (0.161)	0.490*** (0.188)	0.521** (0.230)	3.255*** (0.795)	3.563*** (0.952)	3.874*** (0.997)	2.602*** (0.785)	2.284*** (0.870)	1.965*** (0.727)
	Observations	861	860	836	456	456	433	537	537	514
	CD-test	4.720***	4.335***	4.462***	1.512	1.861*	0.087	-1.556	-1.706	-1.434
	<i>Equity-Assets</i>	0.387* (0.219)	0.375 (0.230)	0.391 (0.249)	-14.03 (11.93)	-12.99 (11.44)	-6.534 (5.725)	-7.235 (6.718)	-8.768 (7.407)	-4.398 (2.925)
	Observations	861	860	836	456	456	433	537	537	514
	CD-test	2.518**	2.496**	2.327**	5.311***	4.212***	3.809***	-0.514	-0.575	-0.097
	<i>Equity-Balance</i>	-0.373** (0.184)	-0.416** (0.205)	-0.382* (0.210)	-2.028*** (0.649)	-2.312*** (0.543)	-2.379*** (0.826)	-1.157* (0.669)	-0.726 (0.623)	-0.536 (0.881)
	Observations	861	860	836	456	456	433	537	537	514
	CD-test	3.411***	3.173***	2.846***	1.842*	1.465	-0.313	-1.343	-1.535	-1.031
	<i>Equity-Mktcap</i>	0.191 (0.182)	0.213 (0.172)	0.250 (0.191)	0.939*** (0.256)	0.944*** (0.282)	0.943** (0.375)	0.183 (0.230)	0.217 (0.235)	0.287 (0.301)
	Observations	861	860	836	456	456	433	537	537	514
	CD-test	4.344***	4.164***	3.829***	4.059***	1.949*	2.998***	0.160	-0.626	-0.833
	<i>Equity-Liabilities</i>	-0.841* (0.476)	-1.031* (0.581)	-1.095* (0.629)	4.020*** (0.824)	2.955** (1.355)	0.603 (2.380)	2.852*** (0.823)	1.199 (2.030)	-0.409 (1.776)
	<i>Mktcap</i>	0.590*** (0.166)	0.733*** (0.204)	0.800*** (0.216)	-0.308 (0.198)	-0.062 (0.307)	0.076 (0.548)	-0.191 (0.255)	-0.113 (0.225)	0.298 (0.535)
	Observations	884	860	836	479	456	433	560	537	514
	CD-test	2.172**	1.353	1.915*	1.744*	0.306	-0.989	-0.989	-1.144	-0.764

*Notes:* This table examines the long-term impact of the equity market openness on interdependencies. We also check the robustness of the findings by building a new variable, *Equity-MktCap*, that divides foreign equity holdings by market capitalization. We report separate results for the comovements (i) among advanced markets, (ii) among emerging markets, and (iii) between developing and developed markets. The dependent variables are our baseline measures of comovements (*PCA* and *PCA-emerging*). The results are based on the CS-DL model with two lags of the variables and the CSA. Standard errors are in parentheses. The signs \*, \*\*, and \*\*\* indicate significance at the 10, 5, and 1% level, respectively.

## Appendix 2.8. Excluding tax-havens

Table 2.18. Excluding tax-haven countries—Advanced markets

<i>Panel A: CS-ARDL with one lag and contemporaneous CSA</i>											
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
<i>Trade-GDP</i>		0.576*		0.950***		0.886**		0.628**	0.802**	0.852**	0.981**
		(0.331)		(0.261)		(0.352)		(0.303)	(0.339)	(0.432)	(0.394)
<i>Trade-de-jure</i>	1.252**			0.806**	0.680		1.425**	0.617*	1.485***		1.771***
	(0.518)			(0.329)	(0.425)		(0.610)	(0.356)	(0.537)		(0.507)
<i>Equity-Liabilities</i>		-1.169*	-0.824		-0.569		-0.509	-0.616		-1.253*	-0.963
		(0.634)	(0.762)		(1.050)		(1.053)	(0.804)		(0.749)	(0.809)
<i>Capital-de jure</i>	0.361		0.352			0.589	-0.223		-0.220	-0.287	-0.973**
	(0.389)		(0.275)			(0.375)	(0.328)		(0.449)	(0.289)	(0.396)
<i>MktCap-GDP</i>		0.733***	0.727***		0.493		0.473	0.461*		0.780***	0.494*
		(0.167)	(0.233)		(0.373)		(0.353)	(0.273)		(0.200)	(0.269)
N	675	657	657	675	657	675	657	657	675	657	657
n	18	18	18	18	18	18	18	18	18	18	18
Tbar	38.95	37.99	37.99	38.95	37.99	38.95	37.99	37.99	38.95	37.99	37.99
ECT	-0.88***	-0.97***	-0.91***	-0.94***	-0.93***	-0.90***	-0.94***	-1.00***	-0.94***	-0.98***	-1.02***
MG-test	4.232***	12.14***	3.349***	7.127***	23.08***	7.130***	8.159***	5.123***	8.498***	10.89***	5.726***
CD-test	-0.601	-0.277	0.172	-0.512	-0.550	1.048	-0.742	-0.631	-0.575	-0.229	-0.627
<i>Panel B: CS-DL with one lag and contemporaneous CSA</i>											
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
<i>Trade-GDP</i>		0.483		0.942***		0.814**		0.526	0.795**	0.739*	0.872**
		(0.327)		(0.267)		(0.320)		(0.330)	(0.337)	(0.413)	(0.415)
<i>Trade-de-jure</i>	1.111**			0.784***	0.735*		1.362**	0.717**	1.367***		1.692***
	(0.463)			(0.298)	(0.378)		(0.535)	(0.352)	(0.472)		(0.479)
<i>Equity-Liabilities</i>		-1.121*	-0.668		-0.328		-0.364	-0.401		-1.277*	-0.951
		(0.593)	(0.723)		(0.894)		(0.942)	(0.727)		(0.677)	(0.761)
<i>Capital-de jure</i>	0.457		0.380			0.629*	-0.177		-0.0870	-0.205	-0.822**
	(0.383)		(0.270)			(0.343)	(0.329)		(0.412)	(0.285)	(0.385)
<i>MktCap-GDP</i>		0.693***	0.622***		0.355		0.393	0.373		0.757***	0.503*
		(0.163)	(0.227)		(0.309)		(0.316)	(0.241)		(0.200)	(0.266)
N	675	657	657	675	657	675	657	657	675	657	657
n	18	18	18	18	18	18	18	18	18	18	18
Tbar	38.95	37.99	37.99	38.95	37.99	38.95	37.99	37.99	38.95	37.99	37.99
MG-test	13.27***	8.138***	11.28***	8.372***	14.49***	8.960***	12.52***	5.374***	6.163***	7.687***	5.004***
CD-test	-0.717	-0.461	0.493	-0.570	-0.606	1.012	-0.727	-1.097	-0.800	-0.242	-1.205

*Notes:* This table simultaneously analyzes the long-term impacts of trade and financial links on advanced market (excl. tax-havens) interdependencies, using multivariate regressions. We add a variable that captures the valuation effect and the level of financial development (*MktCap-GDP*). Standard errors are in parentheses. \*, \*\*, and \*\*\* indicate significance at the 10, 5, and 1% level, respectively.

## Chapter 3

# Interconnectedness of the Insurance Sector: a Long-Term Perspective

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This chapter was presented at the Dauphine Economics Ph.D. Workshop (Paris, 2018), the EconWorld Conference (Seville, 2019), and the Second Dauphine Finance Ph.D. Workshop (Paris, 2019).

### 3.1. Introduction

Interconnectedness represents the linkages with other parts of the financial system and the real economy, which can serve as a channel for shock propagation and amplification (IAIS, 2018). After the 2007–2009 global financial crisis (GFC), interconnectedness has become a key component of the macroprudential supervision of the insurance sector, along with the size, global activity, asset liquidity, and substitutability of firms. Historically, economists and policymakers have paid little attention to the risk associated with the interconnectedness of the insurance sector and considered systemic risks<sup>11</sup> to be mostly confined to the banking sector. However, the GFC highlighted the vulnerability of the insurance sector to external shocks and its potential to spread disturbances to the rest of the economy. At the peak of the crisis, the US government had to bail out the American International Group (AIG), which threatened to collapse and disrupt the entire financial system. Similarly, two other US insurers, Hartford and Lincoln National, as well as Aegon in Netherlands and Ethias in Belgium, asked for government support.

In the aftermath of the crisis, the authorities decided to strengthen the regulation of the insurance sector by introducing new micro and macroprudential measures. The macroprudential supervision, developed by the Financial Stability Board (FSB) in consultation with the International Association of Insurance Supervisors (IAIS), attaches great importance to insurers' interconnectedness and defines new regulatory measures for “systemically relevant institutions.” In 2013, the FSB published a list of nine global systemically important insurers (G-SIIs)<sup>12</sup> facing enhanced group supervision, higher loss absorbency requirements, as well as group-wide recovery and resolution planning. Given the limitations of this entity-based framework, macroprudential regulation is now moving toward a sector-wide approach based on activities rather than firms (IAIS, 2018). The FSB will assess this new holistic framework and review the need

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<sup>11</sup> According to the Systemic Risk Center, “Systemic risk [...] captures the risk of a cascading failure in the financial sector, caused by interlinkages within the financial system, resulting in a severe economic downturn.”

<sup>12</sup> The list consists of Aegon (added into the list in 2015), Allianz SE, Aviva plc, Axa S.A, Assicurazioni Generali S.p.A. (excluded from the list in 2015), and Prudential plc (UK) in Europe, AIG, MetLife, and Prudential Financial in the US, and Ping An Insurance (Group) Company of China.

for annual identification of G-SIIs in 2022. In this new context, this chapter proposes revisiting some of the critical issues related to the risk posed by insurers' interconnectedness.

First, even though insurers played a central role during the GFC, their status as systemically important financial institutions remain questioned, considering that, historically, insurance crises have been rare and have had limited consequences. The main upheavals arising from the insurance industry were the 1984–1986 US “liability insurance crisis” and the near-collapse of the Lloyd’s insurance market in the early 1990s (Baluch et al., 2011). By contrast, Valencia and Leaven (2012) identify 147 banking crises over the period 1970–2011 for both emerging and advanced countries. However, insurers’ interconnections are likely to have increased over time, both within the financial sector and with the rest of the economy, making the sector more systemically important:

- Insurance companies have expanded their activities across borders. While insurance premium volumes grew at about the same pace as the economy, the weight of insurance and financial services in commercial service exports almost doubled between 1983 and 2019 (from 4.6% to 8.4%).<sup>13</sup> Moreover, the insurance sector has become one of the major institutional investors, holding about 12% of financial assets worldwide (IMF, 2016).
- Insurers are an essential source of funding for banks, as bank bonds represent 18% of the investment portfolio of European insurers (EIOPA, 2014). Moreover, regulatory developments in the 1990s initiated a trend towards a “bancassurance” system. In 2016, the Joint Committee of European Supervisory Authorities identified 83 financial conglomerates in Europe, up from 75 in 2009. It is worth noting that most of the G-SIIs are insurer-led conglomerates.
- Likewise, insurers have engaged in non-traditional and non-insurance (NTNI) activities (i.e., investment banking activities, direct lending, investments via hedge funds, and third-party asset management). NTNI activities increased from 3% of total assets in 2004 to 8% in 2014 for non-life US insurers, and from 2.5% to 4.5% for life insurers (IMF, 2016). Furthermore, life insurers that sell financial products with minimal return guarantees (variable annuities) are under pressure from the current low-interest-rate

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<sup>13</sup> Based on the Sigma reports (Swiss Re) and the IMF Balance of Payments Statistics Yearbook.

environment, which might lead them to take additional risks. In the US, for example, variable annuities grew from \$875 billion in 2003 to \$1.5 trillion in 2015, which represents 35% of U.S. life insurer liabilities (Kojien and Yogo, 2020).

This chapter thus examines whether the interconnectedness of the insurance sector has structurally increased over the last decades or only experienced a sudden rise during the GFC due to the unprecedented intensity of the crisis.

Second, we investigate whether the risk related to interconnectedness is mainly concentrated in the largest insurance firms or spread over the entire insurance industry. Previous studies have found mixed results with regard to this question. Billio et al. (2012) and Chen et al. (2014) show that insurance companies are, in general, a non-negligible source of systemic risk. By contrast, Weiß and Mühlnickel (2014) underline that the size of insurance companies drives their exposure and contribution to the risk of the financial system. Finally, Bell and Keller (2009) argue that only insurers that are widely engaged in non-traditional activities can become systemically important. As macroprudential regulation is evolving from an entity-based to a holistic framework, our study proposes reexamining this highly debated issue. In addition, we examine whether some types of insurers (life, non-life, and reinsurers) are more interconnected than others. This analysis complements Kaserer and Klein (2019), who show that some multi-line and life insurers are as systemically important as the riskiest banks.

Finally, some studies (e.g., Thimann, 2015), challenge the parallel treatment of the banking and insurance sectors in the entity-based macroprudential regulation. In fact, both the identification criteria of systemically important institutions and the policy measures applied to these entities are very similar. Based on a descriptive comparison of the business model and balance sheet structures of banks and insurers, Thimann (2015) note that, while both institutions interact with the rest of the system as financial intermediaries and investors, banks are more interconnected than insurers with other financial institutions, notably through the interbank market. This chapter studies this issue by comparing the main characteristics of banks and insurers' interconnectedness based on stock market data.

Regulatory authorities have undertaken extensive work to collect data on balance sheet exposures in order to monitor the interconnectedness of the insurance sector (Data Gaps Initiative). However, detailed balance sheet data are not available from a long-term perspective. We

thus explore insurers' interconnections based on stock price comovements. Such a substitution is possible under the assumption that stock price interdependencies reflect the fundamental links between companies. This hypothesis has been tested at the country level by several empirical studies both in the short- and in the long-run (see, among others, [Forbes and Chinn, 2004](#), and [Chapter 2](#)). [Brooks and Del Negro \(2006\)](#) also report firm-based evidence that international activities positively influence international factor loadings and negatively impact local factor loadings.

Our empirical analysis is based on individual stocks and local industry portfolios from 16 developed markets. We develop an interconnectedness measure using a multifactor asset-pricing model with time-varying loadings and time-varying factor variance. Our indicator of interconnectedness is complementary to recently developed measures of systemic risk (see [Section 3.2](#)). Whereas systemic risk measures can assess the extent of losses due to interdependencies during periods of distress, our indicator enables us to capture the potential strengthening of insurers' interlinkages over the past four decades. Our approach may help explain why some companies experienced greater distress during the GFC and assist in determining whether the likelihood of insurance crisis has increased over time. Indeed, [Berger and Pukthuanthong \(2012\)](#), among others, note that the probability of market crashes is linked to the level of systematic risk. Moreover, [Bierth et al. \(2015\)](#) show that insurers' interconnections are one of the main determinants of the vulnerability of the insurance sector in distressed periods.

Our method allows us to disentangle the relative exposures of insurers and banks to (i) the rest of the financial sector and (ii) the real economy. This breakdown of firms' interconnections between (financial) counterparties and macroeconomic exposures is consistent with the approach developed by the regulator to identify G-SIIs ([IAIS, 2016](#)). Our method can be used to reexamine the findings of [Thimann \(2015\)](#) based on stock price comovements rather than balance sheet data. Finally, we apply our framework to (i) the stocks issued by the largest insurers and (ii) a set of local insurance portfolios to examine whether the risk of interconnectedness is concentrated in the largest insurance firms or spread across the entire insurance industry.

The results highlight that the interconnections of both the largest insurance firms and the rest of the insurance sector have significantly increased over time. By contrast, the interdependencies of non-financial firms have remained more stable. We also find that the intercon-

nectedness of the largest insurers is statistically and economically higher than that of (i) the largest non-financial firms and (ii) the rest of the insurance sector. Moreover, while the interconnectedness of the insurance sector remains lower on average than that of the banking sector, the largest insurance companies are as interconnected as the largest banks. Finally, banks seem more exposed to the rest of the financial sector, while insurance companies are more connected with non-financial sectors. These findings suggest that both entity-based macroprudential regulation and the new holistic framework may be relevant to address the rise in insurers' interconnectedness. We also stress that distinct regulatory measures may be needed to handle the particular features of banks and insurers' interconnections.

The rest of the chapter is structured as follows: [Section 3.2](#) reviews the related literature; [Section 3.3](#) introduces the methodology and describes the data; [Section 3.4](#) details the results of our empirical analysis; [Section 3.5](#) presents the robustness tests; [Section 3.6](#) concludes.

## 3.2. Related literature

This section reviews the literature on insurers' interconnectedness and systemic risk. We focus on papers based on asset price comovements. In line with the efficient market hypothesis, these papers assume that asset prices reflect all available and relevant information about the fundamental links between companies.

An initial body of work focuses on the interdependencies of insurance companies within the financial system. Based on a variance decomposition approach, [Houston and Stiroh \(2006\)](#) show that the comovements across insurance companies strengthened from 1975 to 2005 in the United States. [Billio et al. \(2012\)](#) propose several measures of interdependencies based on Granger-causality networks among insurance companies, hedge funds, banks, and broker/dealers. The authors emphasize the rise in comovements among financial institutions during the GFC. They also show that the insurance and banking sectors are larger shock transmitters than the rest of the financial industry. Using Granger causality tests, [Chen et al. \(2014\)](#) examine the links between insurance companies and banks based on credit default swap spreads and intraday stock prices. They find evidence of bidirectional causality between banking and insurance shocks from 2002 to 2008. They also note that banks tend to spread more shocks and

over longer periods than insurers. Based on a multivariate GARCH framework, [Elyasiani et al. \(2015\)](#) investigate the interconnectedness between the banking and insurance sectors in the United States, the United Kingdom, Europe, and Japan from 2003 to 2009. They find high return and volatility cross-border spillovers both within and across the banking and insurance equity indices. Their results also suggest that, during the GFC, the spillovers from banks increased more significantly than those from insurers. Finally, [Malik and Xu \(2017\)](#) study the interdependencies across global systemically important banks and insurers and reveal the existence of strong regional clusters.

The literature has also developed systemic risk measures based on extreme dependence and loss in asset prices. Some indicators, such as the marginal expected shortfall (MES; [Acharya et al., 2012](#)), assess the vulnerability of financial institutions to external shocks in distressed periods. Others, such as the Delta-conditional value at risk ( $\Delta\text{CoVaR}$ ; [Adrian and Brunnermeier, 2016](#)) and the systemic risk index/capital shortfall (SRISK; [Brownlees and Engle, 2016](#)), measure the contribution of each financial institution to the risk of the financial system. [Bieth et al. \(2015\)](#) analyze the exposures and contributions of 253 life and non-life insurers to the distress of the financial system using the MES, SRISK, and  $\Delta\text{CoVaR}$  indicators. They show that the systemic risk of the insurance sector is relatively small but peaked during the GFC. They also note (i) that insurers' interconnectedness is a significant driver of insurers' vulnerability during crises and (ii) that the contribution of insurers to the distress of the financial system depends on their leverage, loss ratios, and funding fragility. [Berdin and Sottocornola \(2015\)](#) compare the systemic risk of a sample of 60 European insurers, banks, and non-financial firms using the MES and  $\Delta\text{CoVaR}$  measures. They highlight that (i) financial institutions are more systemically relevant than non-financial firms, (ii) the banking sector contributes more to the risk of the whole financial system than the insurance sector, and (iii) the systemic risk of the insurance sector is positively related to its involvement in non-traditional insurance activities. Based on a sample of European financial institutions, [Gehrig and Iannino \(2018\)](#) indicate that, since 2016, the exposure of the insurance sector to systemic risk has become larger than that of the banking sector. In a difference-in-differences setting, [Fung and Yeh \(2018\)](#) explore the impact of macroprudential supervision on the systemic risk of the insurance sector. They report that, following the implementation of macroprudential measures in 2013, both the MES and

$\Delta\text{CoVaR}$  measures declined more significantly for G-SIIs than for the rest of the insurance sector. Finally, Kaserer and Klein (2019) show that, whereas the insurance sector as a whole contributes less to the distress of the financial system than the banking sector, some multi-line and life insurers are as systemically important as the riskiest banks.

Our first contribution to the literature is to examine whether insurers' interconnectedness has structurally changed over time. As mentioned above, systemic risk measures are highly dependent on the occurrence of crises and are not appropriate to examine the long-term evolution of insurers' interdependencies. By contrast, our approach is based on an unconditional measure of interconnectedness. Moreover, we rely on a broad sample of developed markets over a long-term horizon to ensure that country specificities and crisis episodes do not bias our results. Second, our study compares the level of insurers' interconnectedness based on (i) the stocks issued by the largest insurance companies and (ii) industry portfolios. This approach allows us to examine whether the risk of insurers' interconnectedness is concentrated in some companies or spread over the whole industry. We also use non-financial firms as a benchmark to study the specificities of insurers' interdependencies. Finally, to the best of our knowledge, this chapter is innovative since it compares the relative exposures of insurers and banks to the rest of the financial sector and the real economy based on stock market data.

### 3.3. Methodology

#### *3.3.a. Interconnectedness measure*

In the absence of detailed balance sheet data, stock market comovements can be used as a substitute to measure fundamental interdependencies between firms. The reliability of these market-based measures depends on the assumption that stock market comovements reflect real links between companies. Chapter 2 tends to validate this hypothesis in the long run for advanced market economies. Besides, market data are available at a daily frequency and cover many sectors over extended time frames. Market-based measures also provide a synthetic metric of interconnectedness that captures both the intensity of fundamental linkages between companies and their impact on the intrinsic values of the firms. Finally, market returns are supposed to reflect information more rapidly than indicators based on balance sheet data.

Our interconnectedness measure is based on the concept of systematic risk. It is estimated through a multifactor linear asset-pricing model with time-varying factor loadings and time-varying factor variance. It is an extension of the CAPM framework, which includes a broader set of systematic risk factors. Including several factors provide a more precise breakdown of companies' exposures than single-factor models. Multifactor models are also supposed to be more appropriate to capture the plurality of the links between sectors and firms. Our measure captures the exposures of each firm to the shocks stemming from (i) its respective industry and (ii) the rest of the economy. This measure has the advantage of being comparable across sectors, countries, and periods, allowing us to examine the dynamics and specificities of insurers' interconnectedness.

Factor selection is an important part of the analysis. The selected regressors represent industry (financial in the case of the insurance sector), and economic (the rest of the market) shocks at the local, regional, and global scales. These factors are described by equity portfolios that cover more than 75% of the stocks of a given industry or market at a specific scale (i.e., a country, a region, or the world). Our final set of factors consists of three economic and two industry factors. Local industry indices and individual securities are the dependent variables. Following the asset-pricing literature, we have limited the number of factors to five to preserve the interpretability of the regressors and avoid overfitting issues. In [Section 3.5](#), we test the ability of the model to capture the comovements across our sample and compare its performances with alternative specifications (three- and seven-factor models).

Our observable factor model provides us with some easily interpretable results. For instance, it can distinguish between the linkages of the insurance sector with other financial institutions (counterparty exposures) and those with non-financial sectors (macroeconomic exposures). It differs from that proposed by [Billio et al. \(2012\)](#) based on principal components. Indeed, while [Billio et al. \(2012\)](#) estimate the loadings of a group of insurers to a set of common international factors, we investigate the exposures of each insurer to a specific set of local, regional, and global factors. Taking into account local factors is important for two reasons. First, the results presented in [Chapter 1](#) indicate that firms used to be mostly domestically integrated. [Chaieb et al. \(2018\)](#) also show that including a country factor helps to capture the factor structure of stock returns. Second, investment portfolios of insurance companies are usually home-biased,

and insurance activities might be less globalized than other financial activities due to strong national specificities (Thimann, 2014).

The following equation governs our multifactor asset-pricing model:

$$R_{i,t} = \alpha_i + \sum_{j=1}^5 \beta_{i,j} F_{i,j,t}^\perp + \varepsilon_{i,t} \quad (3.1)$$

in which  $R_i$ , a  $(T \times 1)$  vector, represents the returns of the local industry index (or the firm)  $i$ ;  $T$  is the number of observations;  $\alpha_i$  is the intercept; and  $F_{i,j}^\perp$  is a  $(T \times 5)$  matrix containing the orthogonalized factors (see Appendix 3.1). Therefore, the covariances between the factors are null, such as  $\text{Cov}(F_{i,h}^\perp, F_{i,g}^\perp) = 0 \forall h \neq g \in [1, 5]$ .  $\beta_{i,j}$  are the factor loadings, and  $\varepsilon_i$  represents the model errors. Factors and residuals are uncorrelated. For each regression, we address the concern of endogeneity by using a specific set of factors that exclude  $R_i$ . Each beta estimate provides exposure to the respective systematic risk factor but does not allow us to aggregate the systematic risk exposures or compare the relative importance of the factors. By assuming that  $\text{Cov}(F_{i,h}^\perp, \varepsilon_{i,t}) = 0$ , the variance of the returns is:

$$\sigma_{R_i}^2 = \sum_{j=1}^5 \beta_{i,j}^2 \sigma_{F_{i,j}^\perp}^2 + \sigma_{\varepsilon_i}^2 \quad (3.2)$$

where  $\sigma_{R_i}^2$ ,  $\sigma_{F_{i,j}^\perp}^2$ , and  $\sigma_{\varepsilon_i}^2$  represent the historical variances of the index (or firm)  $i$ , factor  $j$ , and the regression errors, respectively. This approach makes the aggregation and comparison of factor loadings possible.

We can divide each component of Equation (3.2) by the variance of the dependent variable. Our main interconnectedness measure is thus based on a variance ratio (VR). For each domestic sector (or firm)  $i$ , the interconnectedness measure is the percentage of the variance of the local industry index (or firm) explained by the systematic risk factors (see Equation 3.3). The indicator is bounded between 0 and 1. Small values characterize poorly interconnected sectors (or firms), while high values indicate that the sector (or the firm) is strongly exposed to industry and non-industry shocks.

$$VR_i = \sum_{j=1}^5 \frac{\beta_{i,j}^2 \sigma_{F_{i,j}^\perp}^2}{\sigma_{R_i}^2} \quad (3.3)$$

VR provides a consistent summary of the exposure to multiple risk factors. It also enables us to examine the evolution of interdependencies over time. However, this indicator can be affected by shifts in the variance of the factors and the dependent variable. We thus perform a robustness test by examining the evolution of VR by setting either the betas or the variances to their sample mean. We also directly examine the value and the dynamics of each factor loading (see Section 3.5).

Moreover, VR is not appropriate for comparison across countries and sectors, as discrepancies in idiosyncratic variance levels ( $\sigma_{\varepsilon_i}^2$ ) can affect the value of the indicator. This bias can be substantial in the case of industry indices. Indeed, the level of idiosyncratic variance of a portfolio partly depends on (i) the number of assets and (ii) the benefits of portfolio diversification. To control for this potential bias, we also construct a measure of interconnectedness based on the absolute level of systematic variance (VL; see Equation 3.4).

$$VL_i = \sum_{j=1}^5 \beta_{i,j}^2 \sigma_{F^{\perp_{i,j}}}^2 \quad (3.4)$$

### 3.3.b. Estimation procedure

The assumption of constant parameters is rarely verified in asset pricing models (e.g., Bos and Newbold, 1984). We test the null hypothesis that factor loadings are fixed over the sample period (Elliott and Müller, 2006). In contrast with previous studies, Elliott and Müller (2006) propose a test that is valid for a wide range of possible departures from the stable model (i.e., many or few breaks, clustered breaks, regular breaks, or smooth variations in the parameters). We check the stability of the coefficients for every local insurance index. We first perform the test for each factor separately and then for all regressors simultaneously (see Equation 3.1). The assumption that all coefficients are fixed is always rejected at the 1% level (see Table 3.11). Thus, we estimate the factor model using rolling window linear regressions.

This method is easily implementable since assumptions regarding the dynamics of the coefficients are not required (Fama and MacBeth, 1973). However, it is difficult to determine the appropriate length of the rolling window, which must be wide enough to estimate precise parameters and short enough to avoid smoothing out important evolutions. Lewellen and Nagel

(2006) argue that short windows provide conditional parameters without the need to specify conditioning information, as long as the coefficients are relatively stable within the window. Note that other dynamic estimators based on structural assumptions exist, but standard historical betas yield lower out-of-sample estimation errors (Hollstein and Prokopczuk, 2016). We arbitrarily fix a one-year window (52 observations) and test the robustness of the results based on two-year (104 observations) and six-month (26 observations) windows. The standard errors are robust to heteroscedasticity and autocorrelation up to a lag of four (Newey and West, 1987).

Estimating many parameters using relatively short time-windows might lead to estimation errors. We follow Vasicek (1973), who suggests shrinking each historical estimate toward a prior, depending on the relative precision of the historical coefficient ( $\beta_{i,j}^{hist}$ ) and prior ( $b_{sect,j}$ ). As the value of each coefficient might be dependent on the variance of the underlying series, we directly apply the shrinkage approach to each component ( $VR_{i,j}^{hist}$ ) of our interconnectedness measure. To obtain a posterior belief of the estimator ( $VR_{i,j}^{Shr}$ ), we combine the historical ratio with the prior ( $VR_{sect,j}$ ), following Equation (3.5):

$$VR_{i,j}^{Shr} = \frac{\sigma_{b_{sect,j}}^2}{\sigma_{\beta_{i,j}^{hist}}^2 + \sigma_{b_{sect,j}}^2} VR_{i,j}^{hist} + \frac{\sigma_{\beta_{i,j}^{hist}}^2}{\sigma_{\beta_{i,j}^{hist}}^2 + \sigma_{b_{sect,j}}^2} VR_{sect,j} \quad (3.5)$$

where  $\sigma_{\beta_{i,j}^{hist}}^2$  and  $\sigma_{b_{sect,j}}^2$  are the variances of the coefficients  $\beta_{i,j}^{hist}$  and  $b_{sect,j}$ , respectively. Following Karolyi (1992), we use a specific (informative) prior for each sector-factor pair. Each prior ( $b_{sect,j}$  and  $VR_{sect,j}$ ) are respectively computed as the cross-sectional average of all the (i) historical estimates and (ii) variance ratios associated with a given sector (e.g., the insurance sector) and a given risk factor (e.g., the global economic factor). Consequently, when the variance of the estimator is high compared to that of the respective prior, the interconnectedness measure is strongly adjusted toward  $VR_{sect,j}$ . We apply the same shrinkage method for the absolute level of systematic variance (VL) and the estimation of each factor loading (see Section 3.5). Since we focus primarily on aggregate sector measures, the shrinkage approach allows us to calculate an outlier-robust average of local interconnectedness indicators. Our main results remain valid without using the shrinkage approach.

*3.3.c. Data*

Our dataset represents the stocks issued by companies from the insurance, banking, basic materials, consumer goods, consumer services, health care, industrials, oil and gas, technology, telecommunications, and utilities sectors. As we want our sample to be relatively homogeneous and available over the long term, we use daily prices from 16 developed markets (Australia, Austria, Belgium, Canada, Denmark, France, Germany, Ireland, Italy, Japan, the Netherlands, Norway, Spain, Switzerland, the United Kingdom, and the United States) between 1973 and 2018.

We use Level 2 and Level 3<sup>14</sup> total return sectoral indices from Datastream Global Equity Indices, which are built according to the FTSE-Dow Jones Industry Classification Benchmark. These indices are market-value weighted and include dividends. Local industry indices from Datastream are interesting for sectoral studies, as each index represents more than 75% of the market value of the related domestic sector at any period. We use Datastream indices instead of those provided by local stock exchanges, as they are constructed according to a unique methodology. There is no overlap between indices, as foreign listings are excluded from each index.

Our market selection represented more than 98% of the world (listed) insurance assets and sales in 1996 (see Table 3.1). Unsurprisingly, this proportion fell to 80–85% in 2017 due to the emergence of large insurance companies in emerging markets. The relative size of each local sector has also changed over time, which may be due to significant waves of mergers and acquisitions within the insurance industry, suggesting a need to examine the insurance sector as a whole.

We also select the ten major companies available since 1973 (in terms of sales and assets<sup>15</sup>, as of 2017) for each sector (see Table 3.4 in Appendix 3.2). Regarding the insurance sector, we ensure that our selection is made up of the five largest life and non-life insurers (including rein-

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<sup>14</sup> More details about the sector components are provided in Table 3.2 (see Appendix 3.2). Insurers and banks are categorized as super-sectors, while basic materials, consumer goods, etc., are categorized as industries. We describe the components of each domestic insurance index (as of 2017) in Table 3.3 (see Appendix 3.2).

<sup>15</sup> For insurance companies, total assets represent the sum of cash, total investments, premium balance receivables, investments in unconsolidated subsidiaries, net property, plant and equipment, and other assets.

urers). In 2018, our group of major insurers represented 25% of the market capitalization of our selection of 16 local insurance sectors. It is worth noting that the dataset is limited to the publicly traded portion of the insurance sector. In the United States, for instance, stock insurers held about 78% of the total cash and invested assets owned by US insurers in 2013, according to the National Association of Insurance Commissioners. Therefore, one of the limitations of our approach is that we cannot assess the interconnectedness of some potentially large mutual insurers.

**Table 3.1.** Description of the selected domestic insurance indices

Countries	Starting point	Total assets (as a % of the world)		Total sales (as a % of the world)	
		As of 1996	As of 2017	As of 1996	As of 2017
United States	1973	31.8	20.8	31.1	22.9
Japan	1973	1.1	18.7	1.9	11.9
United Kingdom	1973	13.8	9.8	12.5	9.0
Canada	1976	3.6	7.9	3.5	5.6
Germany	1973	14.0	6.7	18.0	7.6
France	1977	9.1	6.5	6.9	6.5
Italy	1973	4.3	4.7	6.5	5.4
Switzerland	1973	6.9	3.9	7.7	4.5
Netherlands	1973	4.5	3.3	3.5	2.1
Australia	1973	0.1	0.8	0.2	1.4
Belgium	1973	7.9	0.5	4.7	0.4
Austria	1973	0.3	0.4	0.4	0.5
Spain	1987	0.2	0.4	0.5	0.9
Norway	1980	0.7	0.4	0.6	0.3
Denmark	1973	0.1	0.1	0.2	0.2
Ireland	1989	0.03	0.01	0.04	0.01
All (above countries)		98.6	84.7	98.2	79.4
World		100	100	100	100

*Notes:* For each country, we compare the insurance total assets and sales (as a % of the world) as of 1996 and 2017, the first and last year for which data are available.

We deal with missing data, the non-alignment of time zones, and the differences between currencies following the approach detailed in Chapter 1 (see Section 1.4.a). We calculate weekly returns using stock prices denominated in US dollars to preserve data consistency and for realism purposes.

The main descriptive statistics and diagnostic tests for the 16 domestic insurance indices and the ten largest insurance companies are presented in Table 3.5 (see Appendix 3.2). The statistics are based on weekly returns from 1973 to 2018 (2,345 observations) when data are available. The results indicate the existence of outliers that could impact the regression results.

This fact leads us to winsorize all series at the 1% and 99% percentiles. In Section 3.5, we discuss alternative methods to tackle potential outliers. We also find evidence of serial correlation and heteroscedasticity in the return series, which is accounted for in our estimation method.

### 3.4. Empirical results

This section presents our empirical results. We first apply our methodology to each domestic insurance index, which gives us an overall picture of the extent of insurers' independencies. Special attention is then paid to the interconnectedness of the largest insurance companies. In both cases, we estimate interconnectedness according to the previously discussed methodology (VR and VL) and treat the resulting time series as observable.

#### *3.4.a. Interconnectedness of the entire insurance sector*

First, we focus on the interconnectedness of 16 domestic insurance sectors. As we are mostly interested in the existence of common dynamics in the local insurance sectors of developed countries, we calculate the unweighted cross-sectional average of the domestic interconnectedness measures at each period. We do not employ capitalization-weighted averages, as such would strongly bias the results toward the largest domestic insurance sectors, such as the US, UK, or Japanese insurance industries. More details on the interdependencies of each local insurance sector are provided in Tables 3.7 and 3.8 (see Appendix 3.3).

##### *i. Breakdown of insurers' interconnectedness*

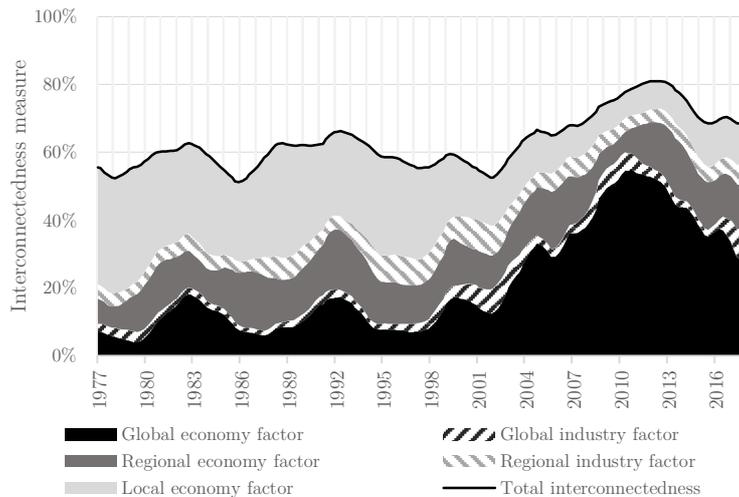
We estimate the interconnectedness (VR) of the entire insurance sector from 1974 to 2018 (see Figure 3.1). For ease of reading, we smooth the series using three-year moving averages of the interconnectedness measure.<sup>16</sup> All statistical tests are applied to the original (unsmoothed) series. We decompose the interconnectedness measure into the percentage explained by each systematic risk factor, namely, the global, regional, and local economic factors, as well as the regional and global industry factors. As indicated in Table 3.6, the total interconnectedness

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<sup>16</sup> The size of the moving average is arbitrary. However, we control and confirm that the use of one-year or five-year moving averages does not change the pattern of the series over the long run.

measure reaches a level of 63% on average, a minimum value of 43% in 2001, and a maximum of 85% in 2012. Hence, the interdependencies of the insurance sector seem to have increased over time, especially during the 2000s.

Regarding the factor loadings, the results indicate that the global and local economic factors are, on average, the strongest sources of insurers' interconnectedness (21% each). By contrast, the regional economic, global industry, and regional industry factors have less influence (12%, 5%, and 3%, respectively). The findings also suggest that the systematic risk exposures of the insurance sector have changed considerably over time. The influence of the local economic factor decreased, especially between 1974 and 2001, while the importance of the global economic factor sharply rose during the 2000s. This finding indicates that the insurance sector has become more globalized over the past four decades, suggesting (i) that domestic insurers have extended their activities beyond national borders or (ii) that the domestic agents insured by local insurers have become more exposed to global shocks.



**Figure 3.1. Breakdown of the interconnectedness (VR) of the average insurance sector**

This figure depicts the evolution (1974–2018, three-year moving averages) of the interconnectedness of the insurance sector (black line) based on 16 local insurance indices from developed countries (unweighted average). The measure is based on a multifactor asset pricing model, which enables us to decompose insurers' interconnectedness into their exposures to financial and non-financial shocks.

*ii. Comparison of the interconnections of insurers, banks, and non-financial firms.*

We compare the level of interconnectedness of insurers, banks, and non-financial firms from 1974 to 2018 (see Figure 3.4 in Appendix 3.3). First, we observe that the three series tend to

follow similar patterns. The average correlation coefficient among the interconnectedness series (VR in first differences) is equal to 73.5%.

We investigate whether the interconnectedness of the insurance sector exhibits some specificities based on paired t-tests (see Table 3.7). More specifically, we compare the mean of each interconnectedness series (VR & VL) from 1974 to 2018. We highlight that the insurance sector is significantly less interconnected than the banking sector ( $-3.7$  and  $-3.1$  points for VR and VL, respectively). On the other hand, VR and VL lead to mixed results when comparing the interconnectedness of the insurance sector with that of non-financial sectors ( $+0.4$  and  $+10.2$  points, respectively). As mentioned above, the VR indicator is less appropriate to compare industry indices, as the level of idiosyncratic variance depends on portfolio diversification benefits. Hence, if local insurance indices are less diversified than other sectoral portfolios, insurers' VR will be biased downward.

Figure 3.4 also suggests that the insurance sector has grown more interconnected than non-financial sectors over time. We confirm this observation by testing for a structural break (Bai and Perron, 2003) in the spread between the interconnectedness measures (VR) of insurers and non-financial firms. This test, presented in Table 3.11 (see Appendix 3.3), indicates that a structural break occurred in August 1998. We perform additional paired t-tests on the two resulting sub-periods (see Table 3.9; Appendix 3.3). Based on VR, we find that the insurance sector used to be significantly less interconnected than non-financial sectors ( $-1.9$  points) from 1974 to 1998. By contrast, it became more interdependent than non-financial sectors ( $+3.3$  points) during the second sub-period (1998–2018). The VL measure also captures this increasing gap ( $+2.3$  and  $+19.1$  points over the periods 1974–1998 and 1998–2018, respectively).

Then, we test for deterministic trends in the interconnectedness series (VR) in Table 3.6. As the assumptions of unit root and autocorrelation are not rejected, we run the Bunzel and Vogelsang (2005) test. This approach is robust to strong serial correlation as well as stationary and nonstationary errors. We report the t-statistics associated with the 5% critical value for the one- and two-tailed tests ( $t_{10\%}$  and  $t_{5\%}$ , respectively), as the most likely alternative hypothesis is that interdependencies have grown over time.

The results indicate that the interdependencies of the insurance and banking sectors follow significant upward deterministic trends ( $+0.4\%$  annually). By contrast, there is no such evi-

dence for the average interdependencies of non-financial sectors (+0.2% per year). This finding suggests that some structural changes in the insurance sector (e.g., mergers and acquisitions, involvement in non-traditional activities, or evolution of market conditions) may have led to an increase in insurers' interconnectedness over the past four decades.

*iii. Local specificities*

We check whether the previous results based on aggregate measures conceal some local-specific features. On average, the French and Dutch insurance sectors appear to be the most exposed to common shocks (VL: 87 and 89%, respectively), while the US insurance sector is the least interconnected (35%, see Table 3.8). This result is mainly due to the fact that the French and Dutch insurance sectors are relatively small (five and three firms, respectively) and include the most interconnected insurers in the world, Axa and Aegon (see Table 3.9). Conversely, the US insurance sector has 48 firms, so that the high degree of interconnectedness of some firms is diluted within the sector as a whole.

We reexamine the interconnectedness of each domestic insurance sector compared to the relative local banking and non-financial sectors using paired t-tests. The results, illustrated in Table 3.7, are globally in line with our findings based on the aggregate interconnectedness measures. On average, most of the domestic insurance sectors are significantly less interdependent than the domestic banking sectors, especially the Spanish, Australian, and Belgian insurance sectors based on VR (−12.2, −8.3, and −8.2 points, respectively) and the Irish, German, and US insurance sectors based on VL (−11.5, −11.2, and −10.3 points, respectively).

We also confirm that most of the domestic insurance sectors have become more interconnected than the local non-financial firms over time. Based on VR, our findings indicate that, while 9 out of 16 domestic insurance sectors were significantly less interconnected than the respective non-financial industries between 1974 and 1998, only 1 out of 16 remained significantly less interdependent from 1998 to 2018 (see Table 3.9).

In addition, we examine the trends in the interdependencies of each local insurance index (see Table 3.8). The results indicate that insurers' interconnectedness has increased in all countries except Japan. The linear deterministic upward trend is significant for Australia, Belgium, Canada, France, Germany, the Netherlands, and Spain. We also control that the rise in insur-

ers' interconnectedness remains significant when we exclude some of the local insurance indices from the aggregate measure (see Table 3.13 in Appendix 3.4). To this end, we recompute the trend test by successively excluding one of the domestic insurance indices from the aggregate measure of interconnectedness. The results show evidence of positive and significant deterministic trends for all the resulting series.

Finally, we provide further details on the dynamics of the interconnectedness of the non-financial sectors (see Table 3.8). We note that, apart from the insurance and banking sectors, only the technology and telecommunications sectors have experienced a permanent rise in interdependencies. Therefore, even though the aggregate measure conceals some heterogeneity, our detailed analysis globally confirms the main results.

#### *3.4.b. Interconnectedness of the largest companies*

On the one hand, the interconnectedness of the largest insurers could be lower than that of the whole insurance sector due to a greater ability to pool and diversify risks. On the other hand, the largest insurers are more likely to have closer links with the other financial institutions and the real economy than smaller insurance companies. Moreover, some of the largest insurers have aggressively engaged in NTNI activities, thus increasing their exposure to external shocks. For example, Harrington (2009) shows that the near default of AIG during the financial crisis resulted from the issuance of credit default swaps (CDS). Koijen and Yogo (2017) also indicate that many NTNI activities (e.g., variable annuities, shadow insurance, and securities lending) are highly concentrated. Finally, we check whether some types of insurers (life, non-life, and reinsurers) are more interconnected than others.

##### *i. Comparison of the interconnections of the largest insurers, banks, and non-financial firms*

Figure 3.2 presents the dynamics of the interconnectedness of the largest insurers, banks, and non-financial firms. The results in Table 3.7 show that the largest insurance companies are significantly more interconnected than the largest non-financial firms (+8.1 and +20.5 points for the VR and VL measures, respectively). This difference appears to be both statistically and economically significant. The interconnectedness (VR) of the largest insurers is more than 15%

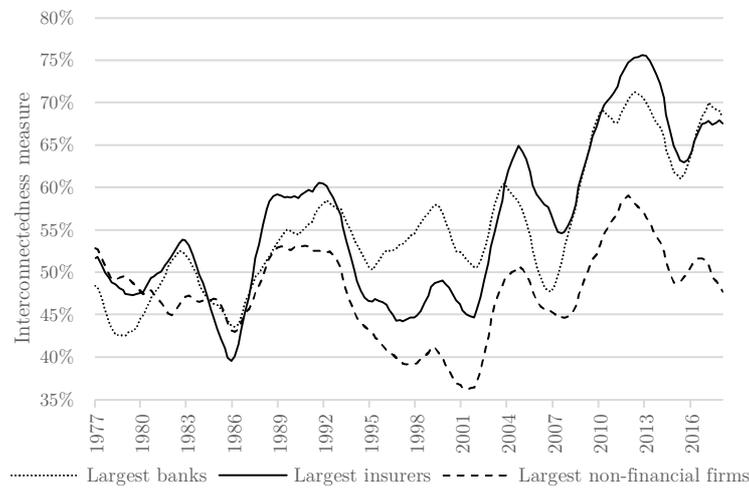
higher than that of the largest non-financial companies over the whole period. On the other hand, there is no significant difference between the interconnectedness of the largest insurers and banks (+0.3 and +1.4 points for VR and VL, respectively). Therefore, contrary to the assumption that insurance companies need to be large to efficiently pool and diversify risks, it seems that the major insurers are more vulnerable to external shocks than smaller ones.

We cannot compare the level of interconnectedness of the largest insurers and the domestic insurance indices using VR, as portfolios mechanically reduce the level of idiosyncratic against systematic risk. Conversely, the results based on the VL indicator are comparable since (i) we apply the same asset-pricing model (see Equation 3.1) to individual and portfolio returns, and (ii) portfolio construction does not impact the absolute level of systematic risk. Based on Table 3.7, we observe that the largest insurers are significantly more interconnected than the rest of the insurance industry (+12.5 points). Moreover, the spread between the interconnectedness of insurers and that of non-financial companies is twice as large for the major firms than for the whole sector (+20.5 vs. +10.2 points respectively). Interestingly, the difference between the level of interdependencies of the major non-financial firms and their respective sectors is only equal to +2.3 points (+8.0 points for banks).

We also examine the primary sources of systematic risk (VR) for the largest insurers and banks (see Table 3.7). Our findings indicate that insurers are more exposed than banks to macroeconomic and market shocks and less interconnected with the other financial institutions (counterparty exposures). Specifically, the largest insurance companies are significantly more exposed than banks to the global, regional, and local *economic* factors (+2.6, +0.6, and +1.2 points, respectively). Conversely, insurers are significantly less exposed to global and regional *industry* shocks (−2.1 and −2.0 points, respectively). In other words, the major insurers are, on average, 12% more exposed to macroeconomic shocks and 28% less interconnected with other financial institutions than the largest banks. These results are in line with those based on the VL indicator. They are also consistent with the findings of Thimann (2015) based on balance sheet data. Insurers' sensitivity to economic and global market fluctuation is likely to be enhanced by their investor status. By contrast, banks are more dependent on short-term funding from the interbank market, which seems to increase their exposure to other financial institutions and, in turn, the risk of a domino effect in the banking sector.

In addition, we test for linear deterministic trends in the interdependence series (VR) of the largest companies (see Table 3.6). While the interconnectedness of the largest insurers and banks follows significant upward deterministic trends (+0.4 and +0.5% annually, respectively), there is no such evidence for the largest non-financial firms. This finding confirms the previous results (Section 3.4.a). In Table 3.8, we also test for trends in the interconnectedness series of each non-financial industry and highlight that none of them have increased significantly over time. Consequently, the difference between the interconnectedness of the largest insurers and non-financial firms has widened over the past decades. In particular, we find that in 2018 the interconnectedness of the largest insurers was 42% higher than that of the largest non-financial firms.

Did the upward trend in the interdependencies of the largest insurance companies drive the rise in the interconnectedness of the entire insurance industry? A simple analysis of the slope of the trend allows us to rule out this hypothesis. First, the interconnectedness level increased at the same rate for the entire insurance sector and the largest insurance institutions (+0.4% per year). Second, the ten major insurance companies only represent 25% of the market capitalization of our selection of 16 local insurance sectors (as of 2018).



**Figure 3.2. Interdependencies (VR) of the largest insurers, banks, and non-financial firms**  
 This figure compares the evolution (1974–2018, three-year moving averages) of the interconnectedness of the largest insurers (solid line), banks (dotted line), and non-financial firms (dashed line) based on individual stocks from developed countries (unweighted cross-sectional averages).

*ii. Life insurers, non-life insurers, and reinsurers*

Insurance companies can be classified as falling into one of three categories: life insurers, non-life insurers, and reinsurers. To investigate the specificities of each type of insurer, we select the ten largest firms in each group from our sample of 16 developed markets (details in Table 3.4 in Appendix 3.2).<sup>17</sup> These 30 insurers represent 40% (as of 2018) of the market capitalization of our selection of 16 local sectors.

Non-life insurers are likely to be less exposed to economic and financial shocks. Indeed, demand for non-life insurance products is relatively inelastic because few substitutes for insurance exist, and some major lines (such as motor) are mandatory. By contrast, demand for life insurance contracts is more dependent on economic and market shocks, as these products are often used as investment vehicles. Moreover, Harrington (2009) underlines that life insurers have higher leverage and are more exposed to policyholder withdrawal than non-life insurers. In addition, a study conducted by The Group of Thirty (2006) indicates that the reinsurance business is not systemically relevant.

Figure 3.5 describes the evolution (1974–2018) of the interdependencies of life insurers, non-life insurers, and reinsurers (see Appendix 3.3). Using paired t-tests (Table 3.12, see Appendix 3.3), we first compare the average level of interconnectedness (VR & VL) of life and non-life insurers over the sample period. Interestingly, the results indicate that non-life insurers are significantly more interconnected than life insurers (+3.9 and +4.4 points for the VR and VL indicators, respectively).

However, we also show that the interconnectedness of life insurers sharply increased during the 2000s (see Figure 3.5). We find evidence of a structural break in the spread between the life and non-life insurers' interdependencies in 2001 (see Table 3.11). We thus compare the average interconnectedness of the life and non-life insurers over the sub-periods 1974–2001 and 2001–2018 in Table 3.12. Our analysis highlights that life insurers became significantly more interconnected than non-life insurers from the first (−8.0 and −10.4 points for VR and VL, respec-

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<sup>17</sup> We rely on the Industry Classification Benchmark, which categorizes each company according to its principal business activity. Hence, some companies, such as Axa, may be classified as non-life insurers while still being involved, to a certain extent, in life insurance activities. Non-life insurance includes full line insurance, insurance brokers, and property and casualty insurance.

tively) to the second (+2.6 and +5.1 points) sub-period. This result is consistent with EIOPA (2018), which reports that the GFC led to a substantial increase in the number of failures in the life insurance segment, while the non-life sector was unaffected. Moreover, Cummins and Weiss (2014) argue that the most systemically relevant activities are the non-core activities conducted by life insurers. Finally, the low-interest-rate environment, which has significantly impacted life insurers' profits, may partly explain this trend. For example, Koijen and Yogo (2020) show that the exposure of the US life insurance sector to 10-year Treasury bond returns has increased over time. By contrast, non-life insurers have suffered less damage, as they can reprice existing contracts and have a shorter investment horizon (IMF, 2016).

The results also indicate that reinsurers are significantly less interconnected than life and non-life insurers (−11.1 and −15.0 points for VR; −25.5 and −29.0 points for VL, respectively). This finding is in line with the study conducted by The Group of Thirty (2006). Nevertheless, the interconnectedness of reinsurers has significantly increased over time (+0.3 points per year from 1974 to 2018; see Table 3.10). This result calls for caution. It is consistent with the analysis of Cummins and Weiss (2014), which points out that, despite historical facts, a reinsurance crisis could severely impact the insurance sector. Indeed, they argue that the reinsurance industry is highly concentrated and interconnected with the rest of the insurance sector.

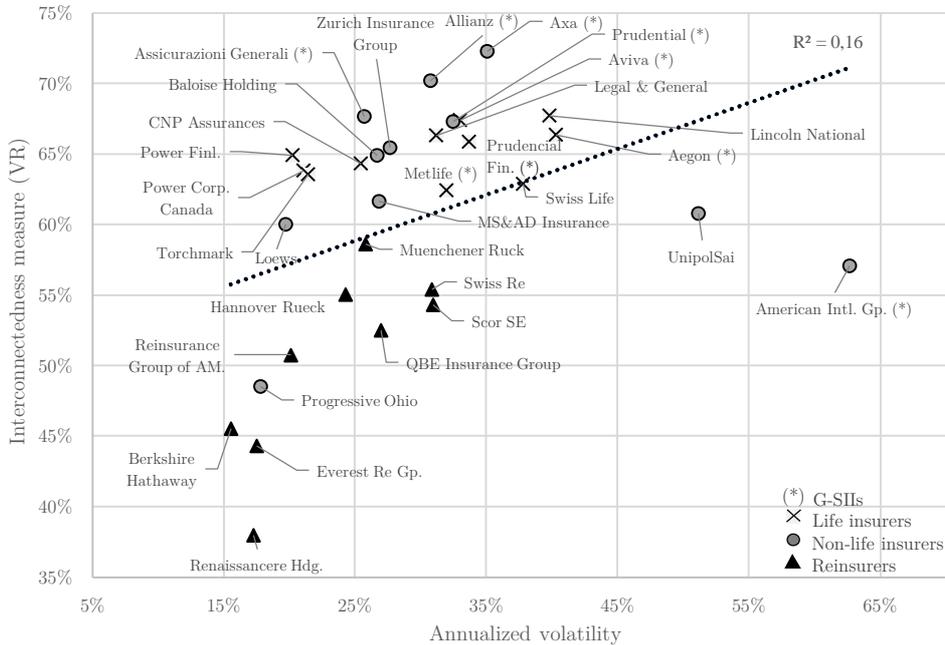
### *iii. Mapping the interconnectedness of the largest insurers*

We plot (i) the average level of interconnectedness (VR) and (ii) the volatility of the returns of each insurance company (see Figure 3.3). We conduct the analysis from 2003 to 2018, the longest time frame for which data are available for all entities. We first check that some outliers do not impact the previous results. With a few exceptions, such as Progressive Ohio, which is classified as a non-life insurer but is less interconnected than most of the reinsurers, the aggregate results presented above are in line with the firm-level analysis.

We also highlight that our interconnectedness measure is able to identify most of the companies designated as G-SIIs by the FSB. Aegon, Allianz, Aviva, Axa, Assicurazioni Generali (excluded from the 2015 list), Prudential, and Prudential Financial all appear among the most interconnected insurers. Lincoln National, which required government support during the GFC, is also part of this group. The only notable exception is AIG, which is significantly less inter-

connected than the other G-SIIs. We assume that the interconnectedness measure of AIG may be biased downward due to the very high level of volatility of its returns. Another reason is that interconnectedness represents no more than 50% of the indicator developed by the IAIS (2016) to identify G-SIIs.

Finally, this chart highlights that our measure of interconnectedness is only weakly related to the level of underlying volatility of insurance stocks. The coefficient of determination between the two variables is equal to 16%. Therefore, although our measure of interconnectedness derived from the volatility of stock returns, it leads to distinct results.



**Figure 3.3. Mapping insurers based on interconnectedness (VR) and volatility**

This figure illustrates the average level of interconnectedness and volatility (i.e., the annualized standard deviation of the returns) of life insurers (squares), non-life insurers (circle), and reinsurers (triangle) from 2003 to 2018 (the longest period for which data from all companies are available). We add data for MetLife and Prudential Financial, which are not included in our selection (of the largest insurers) but are part of the list of G-SIIs.

### 3.5. Robustness tests

This section checks the robustness of the findings using different estimation methods and alternative specifications of the multifactor asset-pricing model.

*3.5.a. Estimation procedure*

There are some outliers in the data (see Section 3.3.c). We addressed this issue by winsorizing all series at the 1% and 99% percentiles. As an alternative, we use a robust regression framework based on iteratively reweighted least squares. The results, presented in Table 3.13, confirm our main findings for both industry indices and the largest firms. Furthermore, the results are robust to ordinary least squares regressions based on non-winsorized returns (unreported). We also note that the series follow close patterns but sometimes diverge during crisis episodes, such as the 1987 stock market crash, which implies that the estimation method must be chosen more carefully when investigating contagion effects.

We also investigate the impact of the shrinkage method (described in Section 3.3.b) on the results. To this end, we reassess our interconnectedness measure without shrinking the parameters (see Table 3.13). Overall, the shrinkage approach does not have any impact on our main results. It is worth noting that the impact of the shrinkage approach was stronger at the beginning of the time frame. This remark is in line with the fact that industry factors are insignificant at the beginning of the time frame (see Section 3.5.c).

We control the robustness of the results to alternative specifications of the rolling window. We reexamine the dynamics of interconnectedness based on two-year and six-month windows (see Table 3.13 in Appendix 3.4). We globally confirm our main results but cannot reject the null hypothesis that there no trend in interdependencies (for insurance indices) based on the two-year window. Besides, as expected, the larger the window, the smoother the series. Hence, short rolling windows are better suited to capture short- and medium-term shifts in insurers' interconnectedness.

*3.5.b. Variance ratio*

Variance ratios are affected by shifts in the variance of the factors and the dependent variable (see Equation 3.3). We argue that an increase in factor loadings better reflects rising insurance' interconnections than a change in variances. We thus test whether the increase in the interconnectedness measure (VR) is due to changes (i) in the variance of the series or (ii) in the factor loadings. To this end, we recalculate VR by setting either betas or variances to their sample mean. We examine the trends of these constrained measures of interconnectedness. We find

significant upward trends in the interconnectedness series when keeping the variances constant. By contrast, there is no such evidence when betas are fixed. Therefore, our results confirm that shifts in the factor loadings drive the rise in insurers' and banks' interdependencies, for both industry indices and firm-level data (see Table 3.14; Appendix 3.4).

We also investigate the dynamics of each factor exposure. We report the results for insurers, banks, and non-financial companies, separately. The analysis reveals that betas have significantly increased over time for all factors (except the local one) and sectors. Interestingly, the slope of the trends is steeper for the insurance and banking sectors than for non-financial sectors. Moreover, the domestic factor loadings of non-financial sectors have decreased more sharply than those of financial industries. Finally, as previously done for the VR and VL indicators, we compare the value of betas for insurers, banks, and non-financial firms based on paired t-tests (see Table 3.14). Based on industry indices, we confirm that the whole insurance sector is more interconnected than the non-financial sectors but less interdependent than the banking industry. By contrast, we find that the largest insurance companies are as interlinked as the largest banks. Again, banks are more exposed to other financial institutions, while insurers have higher exposure to economic factors.

### *3.5.c. Factor model*

The accuracy of the interconnectedness measure depends on the ability of the factor model to capture the plurality of companies' linkages. We first control the significance of the coefficients associated with the five systematic risk factors (see Table 3.15; Appendix 3.4). The measures are based on the unweighted average of the t-values for our samples of industry indices and largest firms, respectively. We compute these measures for the entire sample period (1974–2018) and analyze its evolution by dividing the sample into two equal sub-periods. The standard errors are robust to heteroscedasticity and autocorrelation (Newey and West, 1987). Although the economic factors are significant over the whole time frame, the industry factors are only significant during the second sub-period. This finding highlights that the influence of the industry factors has increased over time, which is consistent with the literature.

Then, we check the ability of our five-factor model to capture the degree of comovements within our sample (see Table 3.16; Appendix 3.4). As a reminder, our approach also aims to

assess the interdependencies between our sample and other stock markets, such as emerging ones. However, strong residual cross-correlations would be the sign of a missing factor in our model. We compare the performances of the five-factor model with alternative specifications (three- and seven-factor models). Specifically, the three-factor model does not include regional factors, whereas the seven-factor model also considers size and value factors at the global scale. The analysis is based on several measures. First, we compare the explanatory power of the models using the adjusted R-squared. Then, we assess the degree of residual comovements using (i) the average of the absolute value of the pair-wise correlations across the residuals and (ii) the 25% and 75% percentile pair-wise correlation coefficients. Finally, we test for weak cross-sectional dependence using Pesaran (2015) test and estimate the strength of the common factors based on the exponent measure of Bailey et al. (2016). We compute these measures from our initial samples (i.e., stock returns of industries and firms) and based on the residuals of the factor models.

First, we find that there is a relatively high degree of comovements both across industry indices and firm-level data. The average absolute pair-wise correlation coefficients are equal to 41.4 and 26.7%, respectively. Moreover, the exponent of the cross-sectional dependence is almost equal to one, which suggests the presence of strong common factors. We show that our baseline factor model is able to capture most of the common risk exposures, as the average absolute pair-wise correlation across residuals decreases to 3.1% and 3.5% for industry indices and the largest firms, respectively. Nevertheless, the null hypothesis of weak cross-sectional dependence is rejected, and the exponent test of Bailey et al. (2016) continues to indicate semi-strong residual comovements. We thus compare the performance of the five-factor model with other specifications.

We consider including international Fama–French factors to our baseline specification. Fama and French (1993) show that size and value factors significantly influence the cross-section of stock market returns. However, our analysis shows that the seven-factor model does not lead to a substantial improvement in the previously defined metrics. The average absolute correlations across the residuals remain equal to 3.1% and 3.5% for industry and firms, respectively. We find a small improvement in the other indicators but still reject the null hypothesis of weak cross-sectional dependence. Therefore, we have decided not to include the size and val-

ue factors in our baseline specification to preserve its ability to distinguish between financial and non-financial loadings. Also, international Fama–French factors are only available from 1990 to 2018.

Including regional factors offers a precise breakdown of the interdependencies of each sector. We examine whether it is a necessary condition to capture the overall level of interconnections across industries and firms. To this end, we compare the results based on three- and five-factor models (see Table 3.16). We find that adding regional factors leads to a substantial improvement of the model performances based on all the previously defined metrics. An additional reason to include regional factors is that we find a structural break in the spread between the interconnectedness measures based on the three- and five-factor models in 2002 (see Table 3.11). During the first sub-period, the results based on the five-factor model are, on average, 4.1 points higher, while during the second sub-period, the differential is only equal to +2.3 points. We conclude that the inclusion of regional factors is essential, especially for long-term analyses. This result also highlights that regional integration was higher from 1974 to 2002 than during the second sub-period.

### 3.6. Conclusion

This chapter studies the evolution and the specificities of insurers' interconnectedness over the past four decades (1973–2018). We assess the interdependencies of insurers, banks, and non-financial firms based on stock market data. Specifically, we use a multifactor asset-pricing model with time-varying factor loadings and time-varying factor variance. Our indicator is complementary to recently developed systemic risk measures and helps determine whether the probability of an insurance crisis has increased over time.

The results indicate that the interdependencies of the whole insurance sector have experienced a significant increase over the past four decades. By contrast, the interconnectedness of non-financial firms has remained more stable over time. This upward trend may result from changes in insurers' business models and balance sheets due to large waves of mergers and acquisitions, the development of global and NTNI activities, and the low-interest-rate environ-

ment. This finding supports the recent proposal of the IAIS to implement new macroprudential supervision based on a holistic framework.

Second, the major insurance companies are significantly more interdependent than the largest non-financial firms and the rest of the insurance sector. This outcome indicates that the risk of insurers' interconnectedness is mostly concentrated in the largest institutions. Therefore, the major insurance companies pose a higher threat to financial stability due to both their size and strong interconnections with the rest of the economy. This result underscores the relevance of the entity-based macroprudential regulation initially implemented by the FSB. Our conclusions are also of interest to investors, as they suggest that the stocks issued by the largest insurers should not be included in equity portfolios for diversification purposes.

Finally, while the insurance sector is less interconnected than the banking sector on average, we show that the largest insurance companies are as interdependent as the major banks. Moreover, insurers and banks are exposed to different sources of risk. Specifically, while insurers are more vulnerable to shocks stemming from the non-financial sectors, banks have stronger links with the rest of the financial industry. This result is consistent with previous findings showing that banks are institutionally linked with the rest of the financial sector through large direct balance sheet exposures. It also suggests that distinct regulatory measures may be needed to handle the features of the interconnectedness of banks and insurers.

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## Appendices

### Appendix 3.1. Factor processing

The factors used to estimate our interconnectedness measure are represented by equity portfolios, extracted from Datastream. To improve the interpretation of each explanatory variable and to prevent potential endogeneity issues, we reprocess the factors. Datastream stock indices share similar components insofar as the world portfolio aggregates the stocks included in regional and local indices. Hence, for each local industry index, we first generate a specific set of non-overlapping factors. For instance, in the case of the German insurance index, we remove (i) the European stocks from the world factor, (ii) the German stocks from the European factor, and (iii) the German insurance stocks from the country factor. We do the same for industry factors.

Second, we use an orthogonalization process to decorrelate each set of non-overlapping factors. Factors must be independent to ensure that the regression captures the specific risk exposures of each local industry index (or firm). We use a combination of hierarchical and symmetric orthogonalization methods. First, the Gram–Schmidt method enables us to build an orthonormal matrix from a free set of factors. It is a hierarchical procedure based on the assumption that there is a top-down causal relationship between factors. Hence, it successively subtracts from each factor its orthogonal projection on the space generated by the superior ranking factors.

By contrast, the symmetric method, first implemented in the finance literature by Klein and Chow (2013), does not impose any hierarchical choice between factors, as it is not sensitive to the order in which the series are orthogonalized. All explanatory variables are thus simultaneously adjusted against each other. Therefore, it can generate the less distinct set of decorrelated factors from the original matrix. This procedure is especially helpful when we can hardly make reliable ranking hypotheses.

Except for a few cases, we use the Gram–Schmidt method, as we can reasonably assume that shock transmission goes from the global to the local factors. To alleviate potential endogeneity issues, we consider that a shock originating from a small country with global impacts is, by definition, a global shock. Since we cannot make reliable assumptions on the direction of

shocks between some industry and economic factors, we use the symmetric procedure, which implicitly assumes that factors equally influence each other.

The Gram–Schmidt orthogonalization procedure is first applied using successive regressions, as follows

$$F_{i,RE,t} = \alpha_{i,RE} + \gamma_{GE}F_{i,GE,t} + \varepsilon_{F_{i,RE,t}}$$

$$F_{i,LE,t} = \alpha_{i,LE} + \delta_{i,GE}F_{i,GE,t} + \delta_{i,RE}\varepsilon_{F_{i,RE,t}} + \varepsilon_{F_{i,LE,t}}$$

$$F_{i,GI,t} = \alpha_{i,GI} + \theta_{i,GE}F_{i,GE,t} + \varepsilon_{F_{i,GI,t}}$$

$$F_{i,RI,t} = \alpha_{i,RI} + \vartheta_{i,GE}F_{i,GE,t} + \vartheta_{i,RE}\varepsilon_{F_{i,RE,t}} + \vartheta_{i,GI}\varepsilon_{F_{i,GI,t}} + \varepsilon_{F_{i,RI,t}}$$

For each industry index  $i$ ,  $F_{i,GE}$ ,  $F_{i,RE}$ ,  $F_{i,LE}$ ,  $F_{i,GI}$ , and  $F_{i,RI}$  represent the global, regional, and local *economic* factors, as well as the global and regional *industry* factors. The residuals of the regressions  $\varepsilon_{F_{i,RE}}$ ,  $\varepsilon_{F_{i,LE}}$ ,  $\varepsilon_{F_{i,GI}}$ , and  $\varepsilon_{F_{i,RI}}$  are the orthogonalized factors. Then, we deal with residual interdependencies using the symmetric orthogonalization method (see Klein and Chow, 2013, for a description of the procedure). Note that the orthogonalization process is important to disentangle the relative risk exposures of each sector but does not impact the aggregate interconnectedness measures.

## Appendix 3.2. Data description

Table 3.2. Typology of the sectors (Industry/Supersector/Sector)

ICB Industry / Datastream Level 2	ICB Supersector / Datastream Level 3	ICB Sector / Datastream Level 4
Oil & Gas	Oil & Gas	Oil & Gas Producers Oil Equipment & Services Alternative Energy
Basic Materials	Chemicals Basic Resources	Chemicals Forestry & Paper Industrial Metals & Mining Mining
Industrials	Construction & Materials Industrial Goods & Services	Construction & Materials Aerospace & Defense General Industrials Electronic & Electric Equipment Industrial Engineering Industrial Transportation Support Services
Consumer Goods	Automobiles & Parts Food & Beverage Personal & Household Goods	Automobiles & Parts Beverages Food Producers Household Goods & Home Construction Leisure Goods Personal Goods Tobacco
Healthcare	Healthcare	Healthcare Equipment & Services Pharmaceuticals & Biotechnology
Consumer Services	Retail Media Travel & Leisure	Food & Drug Retailers General Retailers Media Travel & Leisure
Telecommunications	Telecommunications	Fixed Line Telecommunications Mobile Telecommunications
Utilities	Utilities	Electricity Gas, Water & Multiutilities
Financials	Banks Insurance Real Estate Financial Services Equity Investment Instruments	Banks Nonlife insurance Life Insurance Real Estate Investment & Services Real Estate Investment Trusts Financial Services Equity Investment Instruments Non-equity Investment Instruments
Technology	Technology	Software & Computer Services Technology Hardware & Equipment

Source: Datastream

ICB: Industry Classification Benchmark

**Table 3.3.** Component list of the domestic insurance indices

Country	Insurance company	Country	Insurance company
Australia	Insurance Aus.Group	United Kingdom	Prudential (*)
	QBE Insurance Group		Aviva (*)
	AMP		Legal & General
	Challenger		Old Mutual Limited
	Medibank Private		Rsa Insurance Group
Steadfast Group	Admiral Group		
Austria	Vienna Insurance Group A		St.James's Place Ord
Belgium	Uniqa Insu Gr Ag		Direct Line In.Group
Canada	Ageas (Ex-Fortis)		Beazley
	Manulife Financial		Phoenix Group Hdg.
	Great West Lifeco		Hastings Group Hdg.
	Sun Life Finl.		Hiscox Di
	Power Finl.		Jardine Lloyd Thompson
	Fairfax Finl.Hdg.		Esure Group
	Intact Financial		Just Group
	Power Corp.Canada		Chesnara
	Incl.All.In.& Finl.Svs.		Lancashire Holdings
	E-L Financial		Sabre Insurance Group
Denmark	Tryg		Berkshire Hathaway 'A'
	Topdanmark		Chubb
	ALM Brand	American Intl.Gp. (*)	
France	Axa (*)	Metlife (*)	
	CNP Assurances	Prudential Finl. (*)	
	Scor Se	Marsh & McLennan	
	Coface	Aflac	
Germany	April	Allstate	
	Allianz (*)	Aon Class A	
	Muenchener Ruck.	Travelers Cos.	
	Hannover Ruck.	Progressive Ohio	
	Talanx Aktgsf.	Hartford Finl.Svs.Gp.	
Ireland	Nuernberger Bets.	Willis Towers Watson	
	FBD Holdings	Loews	
Italy	Assicurazioni Generali (*)	CNA Financial	
	Poste Italiane	Principal Finl.Gp.	
	Banca Mediolanum	XI Group	
	UnipolSai	Lincoln National	
	Unipol Gruppo Finanziari	Markel	
	Cattolica Assicurazioni	Arch Cap.Gp.	
Japan	Vittoria Assicurazioni	Arthur J Gallagher	
	Japan Post Holdings	Cincinnati Finl.	
	Tokio Marine Holdings	Torchmark	
	Dai-Ichi Life Holdings	American Finl.Gp.Ohio	
	Ms&Ad Insurance Gp.Hdg.	Everest Re Gp.	
	Sompo Holdings	Unum Group	
	Japan Post Insurance	Alleghany	
	T & D Holdings	Assurant	
	Sony Financial Holdings	Brown & Brown	
	Anicom Holdings	Reinsurance Group of Am.	
Netherlands	Aegon (*)	W R Berkley	
	Nn Group	Assured Guaranty	
	Asr Nederland	Axis Capital Hdg.	
Norway	Gjensidige Forsikring	Brighthouse Financial	
	Storebrand	Erie Indemnity 'A'	
Spain	Protector Forsikring	First Amer.Finl.	
	Mapfre	Hanover Insurance Group	
	Grupo Catalana Occidente	Old Republic Intl.	
Switzerland	Zurich Insurance Group	Primerica	
	Swiss Re	Renaissancere Hdg.	
	Swiss Life Holding	Validus Holdings	
	Baloise-Holding Ag	Berkshire Hathaway 'B'	
	Helvetia Holding N		
	Vaudoise 'B'		

Notes: The list includes 122 insurance companies as of 2018. The sign (\*) indicates that the insurance firm belongs to the list of G-SIIs published by the FSB.

**Table 3.4.** List of the largest companies of each sector

Sector	Company	Country	Sector	Company	Country
Bank	Bank of America	US	Life Insurance	Aegon (*)	Netherlands
	Barclays	UK		Aviva (*)	UK
	Deutsche Bank	Germany		CNP Assurances	France
	HSBC Holdings	UK		Legal & General	UK
	JP Morgan Chase & Co.	US		Lincoln National	US
	Royal Bank Of Canada	Canada		Power Corp.Canada	Canada
	Sumitomo Mitsui Finl.	Japan		Power Finl.	Canada
	Toronto-Dominion	Canada		Prudential (*)	UK
	Unicredit	Italy		Swiss Life	Switzerland
Wells Fargo & Co	US	Torchmark	US		
Basic Materials	Air Liquide	France	Non-Life Insurance	Allianz (*)	Germany
	Anglo American	UK		American Intl.Gp. (*)	US
	BASF	Germany		Assicur. Generali (*)	Italy
	Freeport-Memoran	US		Axa (*)	France
	International Paper	US		Baloise Holding	Switzerland
	Linde	Germany		Loews	US
	Nippon Stl.& Sumit.Mtl.	Japan		MS&AD Insur Gp.Hdg.	Japan
	Rio Tinto	UK		Progressive Ohio	US
	Sumitomo Chemical	Japan		Unipolsai	Italy
Toray Inds.	Japan	Zurich Insur Group	Switzerland		
Consumer Goods	BMW	Germany	Reinsurer	Berkshire Hathaway	US
	Fiat Chrysler Autos.	UK		Everest Re Gp.	US
	Ford Motor	US		Hannover Rueck	Germany
	Honda Motor	Japan		Muenchener Ruck	Germany
	Nestle 'R'	Switzerland		QBE Insurance Group	Australia
	Nissan Motor	Japan		Reinsur Group Of Am.	US
	Procter & Gamble	US		Renaissancere Hdg	US
	Sony	Japan		Scor Se	France
	Toyota Motor	Japan		Swiss Re	Switzerland
Volkswagen	Germany	Talanx Aktgsf	Germany		
Consumer Services	Carrefour	France	Oil & Gas	BP	UK
	Comcast A	US		Chevron	US
	CVS Health	US		Conocophillips	US
	Koninklijke Ahold	Netherlands		Enbridge	Canada
	Kroger	US		Exxon Mobil	US
	Target	US		Repsol Ypf	Spain
	Tesco	UK		Schlumberger	US
	Walgreens Boots	US		Suncor Energy	Canada
	Walmart	US		Total	France
Walt Disney	US	Valero Energy	US		
Health Care	Abbott Laboratories	US	Technology	Apple	US
	Bayer	Germany		Canon	Japan
	Glaxosmithkline	UK		Fujifilm Holdings	Japan
	Humana	US		Fujitsu	Japan
	Johnson & Johnson	US		HP	US
	Medtronic	US		Intel	US
	Merck & Company	US		Inter Bus.Mchs.	US
	Novartis 'R'	Switzerland		Micron Technology	US
	Pfizer	US		Microsoft	US
Roche Holding	Switzerland	Western Digital	US		
Industry	Boeing	US	Telecom	AT&T	US
	Caterpillar	US		BCE	Canada
	General Electric	US		Bt Group	UK
	Hitachi	Japan		Centurylink	US
	Itochu	Japan		KDDI	Japan
	Marubeni	Japan		Nippon Telg. & Tel.	Japan
	Mitsubishi	Japan		Telecom Italia	Italy
	Mitsui	Japan		Telefonica	Spain
	Siemens	Germany		Verizon Commu	US
United Technologies	US	Vodafone Group	UK		
Insurance	Allianz (*)	Germany	Utilities	Duke Energy	US
	Axa (*)	France		E On N	Germany
	Berkshire Hathaway	US		Exelon	US
	MS&AD Insurance	Japan		Kansai Electric Pwr.	Japan
	Muenchener Ruck.	Germany		Nextera Energy	US
	Aegon (*)	Netherlands		PG&E	US
	Aviva (*)	UK		RWE	Germany
	Lincoln National	US		RWE Preference	Germany
	Power Corp.Canada	Canada		Southern	US
Prudential (*)	UK	Tokyo Electric Power	Japan		

*Notes:* This table presents the largest companies in each sector. Our selection is based on (i) a ranking of the firms in terms of assets and sales (as of 2018) and (ii) data availability. (\*) indicates that the insurer belongs to the list of G-SIIs.

**Table 3.5.** Descriptive statistics and diagnostic tests based on return series

Asset	N	Annualized	Annualized	Minimum	Maximum	Skewness	Kurtosis	JB test	Unit root and stationarity tests			Ljung-Box tests	
		returns (%)	standard deviation (%)	weekly Return (%)	weekly return (%)				ADF	PP	KPSS	Returns	Squared returns
Panel A: Local insurance indices													
Australia	2,345	9	24	-25	19	-1.2	8.9	8,330***	-12.0***	-1,878***	0.2	118***	258***
Austria	2,345	9	21	-20	20	0.1	6.8	4,578***	-11.0***	-1,805***	0.3	251***	1,701***
Belgium	2,345	10	35	-103	30	-5.5	112.4	1,245,669***	-12.4***	-2,006***	0.1	230***	505***
Canada	2,225	13	20	-19	18	-0.1	5.7	2,981***	-11.8***	-1,868***	0.2	136***	995***
Denmark	2,345	13	20	-19	24	0.0	5.7	3,145***	-11.7***	-1,825***	0.1	143***	154***
France	2,135	14	28	-20	26	-0.2	4.4	1,718***	-13.2***	-1,550***	0.3	122***	879***
Germany	2,345	11	21	-18	16	-0.4	3.3	1,134***	-12.1***	-1,753***	0.2	190***	901***
Ireland	1,508	1	34	-41	21	-1.8	13.8	12,842***	-10.9***	-1,323***	0.3	100***	1,543***
Italy	2,345	7	24	-16	15	-0.2	1.8	335***	-11.5***	-1,925***	0.2	162***	692***
Japan	2,345	7	23	-19	20	0.2	3.2	991***	-13.2***	-1,786***	0.2	125***	347***
Netherlands	2,345	10	30	-35	27	-0.9	11.7	13,665***	-12.6***	-1,905***	0.2	160***	2,352***
Norway	2,017	8	34	-37	33	-0.7	9.1	7,067***	-11.2***	-1,688***	0.0	124***	1,486***
Spain	1,643	7	29	-52	23	-1.4	19.5	26,536***	-12.9***	-1,337***	0.1	96***	54***
Switzerland	2,345	12	20	-21	18	-0.5	7.6	5,773***	-13.4***	-1,885***	0.2	158***	1,521***
United Kingdom	2,345	11	23	-22	22	-0.4	4.9	2,367***	-13.0***	-1,956***	0.1	78***	767***
United States	2,345	11	16	-19	11	-0.7	7.1	5,162***	-13.3***	-1,905***	0.1	140***	591***
Panel B: Largest insurance companies													
Allianz	2,345	10	26	-21	22	-0.5	4.9	2,402***	-15.4***	-1,846***	0.2	147***	1,846***
Axa	2,135	13	31	-30	26	-0.3	5.2	2,458***	-14.8***	-1,569***	0.3	107***	1,023***
Berkshire Hathaway	2,185	20	19	-19	19	-0.1	6.2	3,532***	-14.0***	-1,737***	1.0***	102***	281***
MS&AD Insurance	2,345	7	28	-22	28	0.4	3.8	1,498***	-16.3***	-1,861***	0.1	83***	192***
Muenchener Ruck	2,345	12	26	-20	26	0.0	4.0	1,549***	-15.3***	-1,716***	0.2	133***	897***
Aegon	2,345	9	30	-42	34	-1.0	14.5	21,044***	-15.5***	-1,951***	0.3	133***	1,720***
Aviva	2,345	7	29	-37	24	-0.7	8.1	6,548***	-15.6***	-1,859***	0.1	78***	1,337***
Lincoln National	2,345	10	30	-60	31	-2.5	37.7	141,495***	-16.3***	-1,911***	0.1	210***	1,343***
Power Corp Canada	2,260	14	22	-18	16	-0.1	3.6	1,240***	-14.1***	-1,707***	0.3	116***	717***
Prudential	2,345	13	29	-25	24	-0.4	5.6	3,147***	-15.8***	-2,016***	0.1	58***	1,426***

*Notes:* This table presents the descriptive statistics and diagnostic tests applied to the weekly return series of 16 domestic insurance indices and the ten largest insurance companies. The null hypothesis of the normality test (Jarque–Bera statistic) is that the series is normally distributed. We report the results of several unit root tests, including the Augmented Dickey–Fuller with drift and trend (ADF), Phillips–Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. We also apply the Ljung-Box Q-tests to the return and squared return series to control for serial correlation and heteroscedasticity. The signs \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively. N is the number of weekly observations.

## Appendix 3.3. Main results

Table 3.6. Interconnectedness measures (VR)—Breakdown by risk factors

Interconnectedness measures and components		Mean (%)	ADF test	Ljung-Box tests	BV (2005)		
					Trend (%)	$t_{5\%}$	$t_{10\%}$
Panel A: Sectoral indices (unweighted average)							
Total interconnectedness	Insurers	63	-2.3	925***	0.4*	(1.2)	(1.8)
	Banks	67	-2.8	785***	0.4**	(2.7)	(3.4)
	Average sector	63	-1.9	862***	0.2	(0.4)	(0.7)
Global economic factor	Insurers	21	-1.8	1,575***	0.8	(0.6)	(1.2)
	Banks	22	-2.1	1,344***	0.7	(0.9)	(1.5)
	Average sector	22	-2.1	1,601***	0.8	(0.9)	(1.6)
Global industry factor	Insurers	3	-3.6**	463***	0.1	(1.1)	(1.6)
	Banks	5	-3.7**	574***	0.2**	(2.1)	(2.6)
	Average sector	4	-2.6	959***	0.1	(0.3)	(0.7)
Regional economic factor	Insurers	12	-4.1***	258***	0.0	(0.3)	(0.3)
	Banks	14	-3.9**	309***	-0.0	(-0.6)	(-0.7)
	Average sector	12	-3.6**	399***	-0.1	(-1.1)	(-1.3)
Regional industry factor	Insurers	5	-2.9	322***	0.0	(0.6)	(0.8)
	Banks	7	-2.6	448***	0.1*	(1.3)	(1.7)
	Average sector	3	-2.5	1,191***	0.1	(0.6)	(1.1)
Local economic factor	Insurers	21	-1.9	1,719***	-0.6**	(-3.4)	(-4.8)
	Banks	20	-2.3	1,724***	-0.6**	(-3.6)	(-5.0)
	Average sector	21	-2.7	1,885***	-0.7*	(-1.6)	(-2.9)
Panel B: Largest companies (unweighted average)							
Total interconnectedness	Insurers	56	-2.8	822***	0.4**	(2.3)	(2.9)
	Banks	56	-3.9**	657***	0.5**	(4.7)	(5.2)
	Average sector	48	-2.7	488***	0.0	(0.1)	(0.1)
Global economic factor	Insurers	20	-2.0	1,461***	0.8	(1.0)	(1.7)
	Banks	17	-2.2	1,388***	0.7*	(1.8)	(2.7)
	Average sector	15	-2.5	1,327***	0.5*	(1.6)	(2.5)
Global industry factor	Insurers	4	-4.0***	457***	0.2*	(1.3)	(1.9)
	Banks	6	-3.4*	642***	0.2**	(2.2)	(2.9)
	Average sector	5	-2.6	1,179***	0.1	(0.2)	(0.6)
Regional economic factor	Insurers	10	-3.1	329***	-0.0	(-0.4)	(-0.5)
	Banks	9	-3.6**	431***	-0.1	(-1.3)	(-1.6)
	Average sector	8	-3.9**	864***	-0.2**	(-2.5)	(-3.2)
Regional industry factor	Insurers	6	-2.5	356***	0.0	(0.3)	(0.4)
	Banks	8	-2.4	605***	0.0	(0.0)	(0.1)
	Average sector	3	-2.8	680***	0.0*	(1.7)	(2.3)
Local economic factor	Insurers	16	-3.1	1,176***	-0.5**	(-2.4)	(-3.5)
	Banks	15	-2.5	1,238***	-0.4*	(-1.1)	(-1.8)
	Average sector	17	-3.1	1,596***	-0.5	(-0.5)	(-1.2)

Notes: This table presents the descriptive statistics and diagnostic tests applied to the interconnectedness measures based on sectoral indices (Panel A) and the largest companies of each sector (Panel B). We also check for linear deterministic trends using Bunzel and Vogelsang, 2005 (BV) test. The 5% and 10% critical values (two-sided) are 2.1 and 1.7, respectively. The signs \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively.

**Table 3.7.** Comparing interconnectedness levels (VR & VL)—Insurers, banks, and non-financial firms

Measure	Insurance vs. Average sector								Insurance vs. Banking sector							
	Local industries				Largest firms				Local industries				Largest firms			
	Diff (VR)	t-stat	Diff (VL)	t-stat	Diff (VR)	t-stat	Diff (VL)	t-stat	Diff (VR)	t-stat	Diff (VL)	t-stat	Diff (VR)	t-stat	Diff (VL)	t-stat
Panel A: All countries (unweighted averages)																
Total connectedness	0.4	(1.2)	10.2***	(5.8)	8.1***	(14.7)	20.5***	(8.1)	-3.7***	(-10.7)	-3.1***	(-3.1)	0.3	(0.6)	1.4	(1.0)
Global economic factor	-1.1***	(-3.9)	4.4***	(3.8)	4.6***	(9.6)	12.0***	(5.9)	-0.6**	(-2.1)	-1.2***	(-3.1)	2.6***	(6.6)	6.4***	(6.1)
Global industry factor	-1.1***	(-7.5)	-0.8***	(-3.8)	-0.6***	(-3.0)	-0.2	(-0.6)	-1.3***	(-7.9)	-1.8***	(-6.0)	-2.1***	(-11.3)	-3.2***	(-8.3)
Regional economic factor	0.4*	(1.9)	2.3***	(5.8)	2.0***	(6.5)	3.1***	(6.8)	-1.4***	(-7.4)	-0.6**	(-2.4)	0.6**	(2.1)	0.3	(1.0)
Regional industry factor	2.2***	(13.9)	1.8***	(12.0)	3.4***	(18.0)	4.1***	(12.8)	-1.6***	(-9.8)	-1.7***	(-7.2)	-2.0***	(-7.2)	-3.4***	(-8.6)
Local economic factor	-0.0	(-0.0)	2.5***	(6.3)	-1.3***	(-6.3)	1.4***	(2.7)	1.1***	(5.4)	2.2***	(5.5)	1.2***	(4.4)	1.3*	(1.9)
Panel B: By country (total connectedness)																
Australia	-7.3***	(-7.7)	0.4	(0.3)		n/a			-8.3***	(-8.5)	-4.5***	(-3.0)			n/a	
Austria	2.4***	(4.4)	2.0	(1.6)		n/a			0.7	(0.7)	-9.3***	(-2.7)			n/a	
Belgium	-0.4	(-0.4)	24.0***	(7.7)		n/a			-8.2***	(-13.2)	-0.1	(-0.1)			n/a	
Canada	-5.6***	(-7.0)	-0.1	(-0.1)		n/a			-6.8***	(-9.0)	-0.7	(-0.7)			n/a	
Denmark	-2.1***	(-3.1)	-0.1	(-0.1)		n/a			-5.2***	(-7.0)	-6.7***	(-4.7)			n/a	
France	-5.6***	(-7.0)	22.9***	(6.2)		n/a			-2.7***	(-3.8)	-3.8	(-1.5)			n/a	
Germany	1.4**	(2.2)	9.8***	(6.2)		n/a			-4.1***	(-6.3)	-11.2***	(-5.6)			n/a	
Ireland	3.0***	(4.0)	16.8***	(3.9)		n/a			-6.5***	(-9.8)	-11.5***	(-3.8)			n/a	
Italy	10.4***	(21.5)	12.5***	(7.1)		n/a			3.4***	(4.7)	-6.6***	(-2.7)			n/a	
Japan	1.0	(1.3)	21.3***	(8.8)		n/a			-2.5***	(-3.5)	-2.0	(0.9)			n/a	
Netherlands	-3.4***	(-4.9)	21.2***	(5.1)		n/a			-2.8***	(-2.8)	15.5***	(4.3)			n/a	
Norway	-3.4***	(-6.4)	9.4***	(4.2)		n/a			-5.5***	(-7.9)	-0.5	(-0.2)			n/a	
Spain	-1.3*	(-1.7)	20.9***	(7.4)		n/a			-12.2***	(-13.0)	-8.1***	(-3.7)			n/a	
Switzerland	4.7***	(7.4)	11.3***	(6.2)		n/a			-1.9***	(-2.6)	-2.1*	(-1.9)			n/a	
UK	1.5***	(2.8)	13.8***	(7.8)		n/a			1.3*	(1.9)	2.9*	(1.9)			n/a	
US	8.9***	(12.7)	0.3	(0.3)		n/a			-0.5	(-0.8)	-10.3***	(-6.8)			n/a	

*Notes:* This table compares the level of interconnectedness of insurers, banks, and the non-financial sectors using paired t-tests. Panel A focuses on the interconnectedness measure for the entire insurance sector. Panel B compares interconnectedness within each country. We report the average spread (Diff) between the interconnectedness series (VR or VL). Based on VR, Diff is expressed in percentage points, while based on VL, it is measured as the absolute level of variance multiplied by  $10^5$ . Test statistics are in parentheses. The signs \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively.

**Table 3.8.** Interconnectedness levels (VR & VL)—Details by countries and sectors

Area	N	Average measure		BV (2005)		
		VR (%)	VL $\times 10^3$ (%)	Trend VR (%)	$t_{5\%}$	$t_{10\%}$
Panel A: Local insurance indices						
Australia	191	65	56	0.9**	(5.9)	(6.9)
Austria	191	61	53	0.3	(0.7)	(1.0)
Belgium	191	63	77	0.6**	(5.2)	(5.8)
Canada	178	62	47	0.9**	(4.6)	(5.4)
Denmark	191	55	47	0.4	(0.8)	(1.2)
France	174	71	87	0.8**	(2.7)	(3.4)
Germany	191	71	61	0.4*	(1.7)	(2.1)
Ireland	118	58	69	0.4	(0.1)	(0.1)
Italy	191	77	77	0.0	(0.2)	(0.3)
Japan	135	71	65	-0.3	(-0.7)	(-1.0)
Netherlands	191	65	89	0.6*	(1.7)	(2.4)
Norway	161	58	73	0.6	(0.8)	(1.3)
Spain	131	63	71	0.9*	(1.1)	(1.7)
Switzerland	191	69	59	0.1	(0.2)	(0.3)
United Kingdom	191	72	64	0.3	(0.6)	(1.0)
United States	191	74	35	0.1	(0.7)	(0.7)
Panel B: Industry indices						
Insurers	191	63	58	0.4*	(1.2)	(1.8)
Banks	191	67	61	0.4**	(2.7)	(3.4)
Basic Materials	191	72	57	0.0	(0.1)	(0.1)
Consumer Goods	191	58	45	0.4	(0.1)	(0.3)
Consumer Services	191	69	43	0.1	(0.5)	(0.7)
Healthcare	191	66	34	-0.2*	(-1.9)	(-2.4)
Industrials	191	71	50	0.5	(0.3)	(0.8)
Oil & Gas	191	64	59	0.2	(0.3)	(0.4)
Technology	191	55	60	0.4**	(3.1)	(3.7)
Telecommunications	191	55	48	0.2**	(2.1)	(2.3)
Utilities	191	55	32	0.2	(0.0)	(0.1)
Panel C: Largest firms						
Insurers	191	56	70	0.4**	(2.3)	(2.9)
Banks	191	56	69	0.5**	(4.7)	(5.2)
Basic Materials	191	59	66	0.0	(0.0)	(0.1)
Consumer Goods	191	47	49	0.1	(0.4)	(0.5)
Consumer Services	191	42	44	-0.2	(-0.3)	(-0.5)
Healthcare	191	47	35	-0.2	(-0.6)	(-0.8)
Industrials	191	56	61	-0.0	(0.1)	(0.2)
Oil & Gas	191	50	47	0.7	(0.6)	(1.2)
Technology	191	41	68	0.0	(0.2)	(0.3)
Telecommunications	191	46	49	-0.1	(0.1)	(0.2)
Utilities	191	41	30	-0.1	(0.2)	(0.4)

*Notes:* This table compares the average interconnectedness measures (VR & VL) (i) across countries (over 1991–2018, the largest period for which all data are available) and (ii) across industries (1974–2018) for both industry indices and the largest firms. We report the annualized trends (%) and t-statistics (in parentheses) based on the linear deterministic trend test of [Bunzell and Vogelsang, 2005](#) (BV). The null hypothesis is that there is no trend in the series. The 5% (\*\*) and 10% (\*) critical values (two-sided) are 2.1 and 1.7, respectively. N is the number of quarterly observations.

**Table 3.9.** Comparing interconnectedness levels (VR & VL)—Insurers vs. non-financial sectors

Measure	Local industries								Largest firms							
	1974-1998				1998-2018				1974-1998				1998-2018			
	Diff (VR)	t-stat	Diff (VL)	t-stat	Diff (VR)	t-stat	Diff (VL)	t-stat	Diff (VR)	t-stat	Diff (VL)	t-stat	Diff (VR)	t-stat	Diff (VL)	t-stat
Panel A: All countries (unweighted averages)																
Total connectedness	-1.9***	(-4.4)	2.3**	(-2.4)	3.3***	(7.6)	19.1***	(5.6)	3.1***	(6.0)	7.2***	(6.3)	13.8***	(23.2)	35.2***	(7.4)
Global economic factor	-2.1***	(-9.7)	-0.6**	(-2.1)	-0.0	(-0.0)	9.9***	(4.3)	0.6**	(2.3)	0.9***	(3.0)	9.1***	(12.3)	24.5***	(6.2)
Global industry factor	-0.6***	(-4.4)	-0.5***	(-5.2)	-1.7***	(-6.3)	-1.1***	(-2.7)	-0.5***	(-4.3)	-0.9***	(-5.7)	-0.7*	(-1.8)	0.5	(0.8)
Regional economic factor	-1.0***	(-5.0)	0.1	(0.4)	2.2***	(6.2)	4.8***	(6.8)	0.8*	(1.8)	1.0**	(2.1)	3.4***	(9.1)	5.5***	(7.5)
Regional industry factor	3.1***	(15.1)	2.0***	(10.3)	1.3***	(6.0)	1.7***	(7.0)	3.8***	(14.6)	3.7***	(8.2)	2.9***	(11.3)	4.7***	(10.1)
Local economic factor	-1.2***	(-3.7)	1.3**	(2.1)	1.5***	(6.6)	3.9***	(8.4)	-1.7***	(-5.2)	2.6***	(2.9)	-0.9***	(-3.6)	0.0	(0.0)
Panel B: By country (total connectedness)																
Australia	-13.8***	(-10.3)	-8.5***	(-6.0)	0.2	(0.3)	10.5***	(4.8)					n/a			
Austria	0.9	(1.1)	-1.6	(-0.9)	4.1***	(7.0)	5.9***	(3.6)					n/a			
Belgium	-7.7***	(-9.4)	5.0***	(5.1)	8.4***	(12.4)	45.4***	(7.9)					n/a			
Canada	-13.6***	(-18.2)	-2.7***	(-3.1)	2.7***	(4.1)	2.3	(0.8)					n/a			
Denmark	-5.2***	(-5.8)	0.9	(0.8)	1.6**	(2.0)	-1.2	(-0.8)					n/a			
France	-13.3***	(-19.0)	4.1**	(2.5)	1.8**	(2.0)	40.2***	(6.3)					n/a			
Germany	-0.9	(-1.0)	7.5***	(4.5)	4.3***	(5.9)	12.5***	(4.6)					n/a			
Ireland	2.6	(1.3)	-2.2**	(-2.4)	3.2***	(4.6)	22.7***	(4.1)					n/a			
Italy	12.3***	(20.6)	6.6***	(4.4)	8.2***	(11.5)	19.1***	(6.0)					n/a			
Japan	4.1***	(3.3)	26.0***	(6.9)	-0.9	(-1.0)	18.7***	(6.2)					n/a			
Netherlands	-8.5***	(-10.9)	0.3	(0.3)	2.4***	(2.8)	44.6***	(5.5)					n/a			
Norway	-5.5***	(-6.8)	6.4***	(2.8)	-1.6**	(-2.5)	11.6***	(3.3)					n/a			
Spain	-5.2***	(-6.1)	13.1***	(5.8)	0.7	(0.7)	24.3***	(6.2)					n/a			
Switzerland	2.3***	(2.7)	1.3	(1.3)	7.7***	(8.9)	22.6***	(6.8)					n/a			
UK	-1.2	(-1.6)	8.4***	(7.1)	4.7***	(8.3)	19.8***	(5.8)					n/a			
US	12.6***	(16.8)	3.9***	(4.6)	4.7***	(4.3)	-3.8**	(-2.5)					n/a			

*Notes:* This table compares the level of interconnectedness of insurers, banks, and the non-financial sectors using paired t-tests. Panel A focuses on the interconnectedness measure for the entire insurance sector. Panel B compares interconnectedness within each country. Based on VR, the spread between the measures (Diff) is expressed in percentage points, while based on VL, it is measured as the absolute variance level multiplied by  $10^5$ . The sub-periods are based on structural break tests, presented in Table 3.11. Test statistics are in parentheses. The signs \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively.

**Table 3.10.** Interconnectedness levels (VR & VL)—Details by firms

Largest firms	N	Average measure (2000–2018)		Robust trend test		
		VR (%)	VL $\times 10^3$ (%)	Trend VR (%)	$t_{5\%}$	$t_{10\%}$
Panel A: Aggregate results						
Life insurers	191	66	85	0.4	(0.8)	(1.3)
Non-life insurers	191	63	79	0.2	(0.8)	(1.2)
Reinsurers	191	51	44	0.3*	(1.4)	(1.9)
Panel B: Life insurers						
Aegon (*)	191	67	112	0.6**	(2.1)	(2.7)
Aviva (*)	191	67	97	0.4	(0.8)	(1.2)
CNP Assurances	79	64	83	1.6	(0.1)	(0.2)
Legal & General	191	66	89	0.3	(0.3)	(0.5)
Lincoln National	191	68	100	0.6**	(2.5)	(3.1)
Power Corp. Canada	178	64	64	0.6**	(2.2)	(2.6)
Power Finl.	139	65	59	1.1**	(3.2)	(4.1)
Prudential (*)	191	67	100	0.2	(0.4)	(0.6)
Swiss Life	126	63	93	1.0*	(1.6)	(2.3)
Torchmark	191	64	52	0.7**	(4.5)	(5.1)
Panel C: Non-life insurers						
Allianz (*)	191	70	92	0.4*	(1.6)	(2.0)
American Intl. Gp. (*)	191	58	76	0.1	(0.9)	(1.0)
Assicurazioni Generali (*)	191	68	84	-0.2	(-0.5)	(-0.7)
Axa (*)	174	72	126	0.6**	(2.2)	(2.8)
Baloise Holding	191	65	75	0.4	(1.2)	(1.6)
Loews	191	60	51	0.1	(0.2)	(0.3)
MS&AD Insurance Gp.Hdg.	135	61	78	-0.2	(-0.3)	(-0.5)
Progressive Ohio	191	49	47	0.1	(1.2)	(1.3)
UnipolSai	191	60	86	0.0	(0.0)	(0.1)
Zurich Insurance Group	191	65	73	0.3	(0.3)	(0.5)
Panel D: Reinsurers						
Berkshire Hathaway	178	45	29	0.4	(1.3)	(1.6)
Everest Re Gp.	92	45	33	0.0	(0.1)	(0.1)
Hannover Rueck	96	55	56	1.2	(0.6)	(1.0)
Muenchener Ruck	191	59	59	0.5**	(2.5)	(3.1)
QBE Insurance Group	191	52	52	0.7**	(4.7)	(5.2)
Reinsurance Group of AM.	105	51	39	1.6**	(2.7)	(3.6)
Renaissancere Hdg.	96	38	28	0.7*	(1.4)	(1.8)
Scor SE	122	54	56	1.2*	(1.2)	(1.9)
Swiss Re	191	56	63	0.1	(0.3)	(0.3)
Talanx Aktgsf	18	n/a	n/a	2.2	(0.0)	(0.0)

*Notes:* This table compares the average interconnectedness measures (VR & VL) of (i) life insurers, (ii) non-life insurers, and (iii) reinsurers (from 2000 to 2018, the largest period for which all data are available). We report the annualized trends (%) and t-statistics (in parentheses) based on the linear deterministic trend test of [Bunzell and Vogelsang, 2005](#) (BV). The null hypothesis is that there is no trend in the series. The 5% (\*\*) and 10% (\*) critical values (two-sided) are 2.1 and 1.7, respectively. N is the number of quarterly observations. (\*) indicates that the insurer belongs to the list of G-SIIs.

**Table 3.11.** Time-varying parameters and structural breaks

Panel A: Test for fixed coefficients in Equation 3.1 (Elliott and Müller, 2006)						
Local insurance index	All coefficients	Local	Industry (Regional)	Regional	Industry (Global)	Global
Australia	-59.8***	-29.1***	-15.0***	-13.7***	-29.3***	-25.4***
Austria	-58.2***	-20.5***	-12.3***	-10.7**	-14.5***	-8.9**
Belgium	-62.0***	-13.7***	-13.9***	-17.4***	-5.0	-17.2***
Canada	-49.3***	-20.3***	-24.1***	-16.2***	-24.1***	-13.4***
Denmark	-41.3***	-14.3***	-6.2	-10.1**	-7.7*	-13.1***
France	-37.3***	-5.6	-6.7	-4.8	-4.8	-5.0
Germany	-47.0***	-26.9***	-11.9***	-12.0***	-7.5*	-11.3***
Ireland	-55.6***	-31.1***	-32.4***	-19.4***	-29.6***	-18.2***
Italy	-50.9***	-6.6	-7.8*	-8.8**	-8.1*	-8.7**
Japan	-74.3***	-33.0***	-24.6***	-25.5***	-11.9***	-16.7***
Netherlands	-84.3***	-35.2***	-45.2***	-43.3***	-33.0***	-30.9***
Norway	-42.1***	-16.9***	-17.3***	-11.5***	-12.8***	-8.0*
Spain	-42.5***	-12.8***	-8.8**	-9.3**	-7.5*	-15.2***
Switzerland	-76.2***	-24.9***	-45.0***	-33.4***	-33.7***	-34.4***
United Kingdom	-39.5***	-7.9*	-13.2***	-7.0	-6.5	-8.7**
United States	-52.9***	-18.2***	-9.9**	-9.9**	-2.9	-7.9*

Panel B: Test for structural break on the interconnectedness series – one break max (Bai and Perron, 2003)

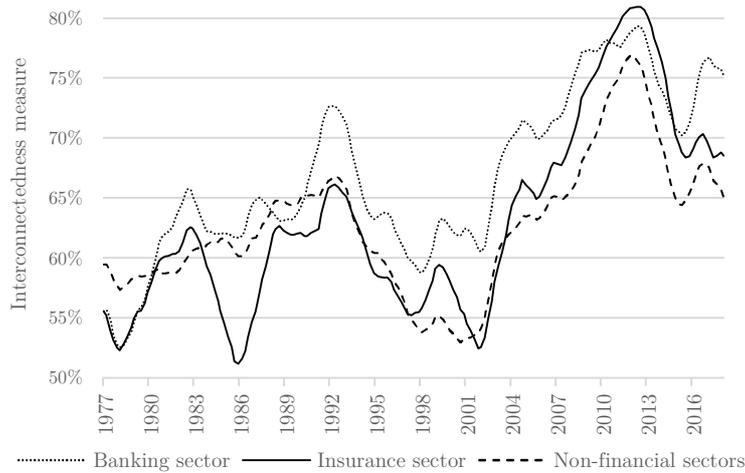
Interconnectedness measure	Break dates	95% confidence intervals
Insurance vs. non-financial sectors	1998:08	1997:12 – 1999:05
Life vs. non-life insurers	2001:11	2000:09 – 2003:09
Five vs. three-factor model	2000:12	1999:10 – 2002:10

*Notes:* Panel A examines whether the factor loadings in our asset-pricing model are stable over time, based on the test of Elliott and Müller (2006). The null hypothesis is that the coefficients are fixed over the sample period. The 1%(\*), 5%(\*\*) and 10% (\*\*\*) critical values are equal to (i) -35.1, -30.6, and -28.6 when all the coefficients can vary over time (first column) and (ii) -11.1, -8.4, and -7.1 when we test each factor separately. Panel B checks the existence of a structural break in the spread between the interconnectedness series. Our approach is based on the structural break test of Bai and Perron (2003), which evaluates a multiple linear regression model with  $m$  breaks ( $m+1$  regimes). This table provides the estimated break dates and 95% confidence intervals.

**Table 3.12.** Comparing interconnectedness levels (VR)—Details by insurer types

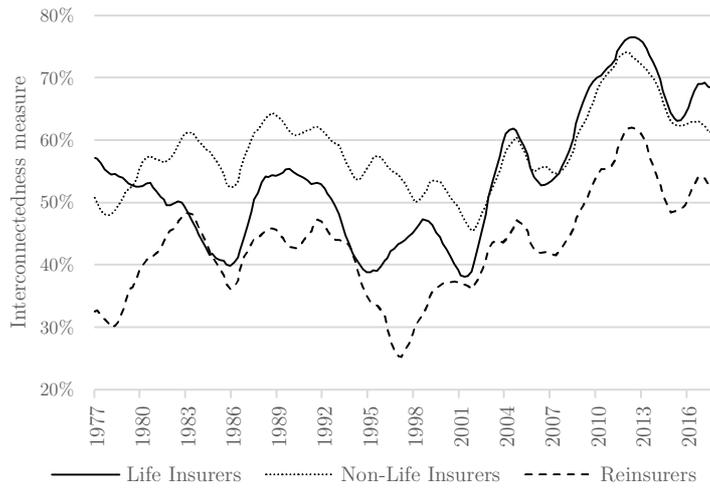
Interconnectedness measure	Life vs. Non-life insurers		Life vs. Reinsurers		Non-life vs. Reinsurers	
	Diff (%)	t-stat	Diff (%)	t-stat	Diff (%)	t-stat
VR	-3.9***	(-6.0)	11.1***	(16.8)	15.0***	(28.0)
VL	-4.4**	(-2.3)	25.5***	(9.2)	29.0***	(17.9)
VR (1974–2001)	-8.0***	(-10.0)	8.6***	(9.2)	16.6***	(22.5)
VL (1974–2001)	-10.4***	(-4.0)	18.0***	(6.4)	28.4***	(17.5)
VR (2001–2018)	2.6***	(4.7)	15.1***	(25.7)	12.5***	(19.4)
VL (2001–2018)	5.1**	(2.2)	37.2***	(6.9)	32.1***	(9.2)

*Notes:* This table compares the level of interconnectedness (and its breakdown) for life insurers, non-life insurers and reinsurers using paired t-tests. We report the average spread (Diff) between the interconnectedness series over a given period. The periods are defined based on the structural break tests detailed in Table 3.11 (Panel B). Test statistics are in parentheses. The signs \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively.



**Figure 3.4. Interdependencies (VR) of insurers, banks, and non-financial sectors**

This figure compares the evolution (1974–2018; three-year moving averages) of the interconnectedness of insurers (solid line), banks (dotted line), and non-financial sectors (dashed line). The measures are based on local industry indices from developed countries (unweighted cross-sectional averages).



**Figure 3.5. Interdependencies (VR) of the largest life, non-life insurers, and reinsurers**

This figure compares the evolution (1974–2018; three-year moving averages) of the interconnectedness of the largest life insurers (solid line), non-life insurers (dotted line), and reinsurers (dashed line). The measures are based on individual stocks from developed countries (unweighted cross-sectional averages).

Appendix 3.4. Robustness tests

Table 3.13. Alternative specifications

Panel A: Robustness of the estimation method (VR)																
		Measure		Average value (%)		Trend (%)		$t_{5\%}$		$t_{10\%}$						
Without shrinkage	Industry indices	Insurers		60		0.4*		(1.4)		(2.1)						
		Banks		65		0.4**		(2.8)		(3.6)						
		Average sector		60		0.2		(0.4)		(0.7)						
	Largest firms	Insurers		54		0.5**		(2.5)		(3.1)						
		Banks		54		0.5**		(5.5)		(6.1)						
		Average sector		46		0.0		(0.2)		(0.3)						
Robust regression	Industry indices	Insurers		62		0.4**		(2.1)		(2.8)						
		Banks		66		0.4**		(2.7)		(3.5)						
		Average sector		62		0.2		(0.5)		(0.9)						
	Largest firms	Insurers		55		0.5**		(3.0)		(3.6)						
		Banks		55		0.5**		(5.2)		(5.6)						
		Average sector		47		0.0		(0.1)		(0.2)						
Two-year rolling window	Industry indices	Insurers		62		0.4		(0.6)		(1.2)						
		Banks		66		0.4*		(1.1)		(1.8)						
		Average sector		61		0.2		(0.1)		(0.2)						
	Largest firms	Insurers		54		0.6*		(1.6)		(2.3)						
		Banks		53		0.6**		(5.7)		(6.5)						
		Average sector		45		0.1		(0.1)		(0.2)						
Six-month rolling window	Industry indices	Insurers		67		0.4**		(2.3)		(2.9)						
		Banks		69		0.4**		(3.4)		(4.1)						
		Average sector		67		0.2		(1.1)		(1.4)						
	Largest firms	Insurers		61		0.5**		(2.8)		(3.4)						
		Banks		59		0.4**		(4.5)		(5.0)						
		Average sector		54		0.0		(0.4)		(0.5)						
Panel B: Trend in insurers' interconnectedness (VR)—Robustness to the exclusion of one country																
Excl. country	AU	AT	BE	CA	DK	FR	DE	IE	IT	JP	NL	NO	ES	CH	GB	US
Trend (%)	0.4*	0.4*	0.4*	0.4*	0.4*	0.4*	0.4*	0.4*	0.4*	0.4*	0.4*	0.4*	0.4*	0.4*	0.4*	0.4*
$t_{5\%}$	(1.3)	(1.8)	(1.4)	(1.4)	(1.7)	(1.5)	(1.7)	(1.9)	(1.8)	(1.5)	(1.6)	(1.7)	(1.8)	(1.7)	(1.7)	(1.6)
$t_{10\%}$	(1.9)	(2.4)	(1.9)	(2.0)	(2.3)	(2.1)	(2.3)	(2.5)	(2.5)	(2.1)	(2.2)	(2.3)	(2.4)	(2.4)	(2.4)	(2.3)

Notes: This table controls the robustness of our main results to alternative specifications. Panel A reports the value and the trend of VR estimated (i) without shrinkage (see Section 3.3), (ii) using robust regressions instead of return winsorization, and (iii) based on two-year or six-month rolling windows. Panel B presents the results of Bunnell and Vogelsang, 2005 (BV) test applied to the interconnectedness of the entire insurance sector. We compute the test 16 times by successively excluding one country from the aggregate measure of interdependencies. The signs \* and \*\* indicate significance at the 10 and 5% level, respectively. Abbreviations: Australia (AU); Austria (AT); Belgium (BE); Canada (CA); Denmark (DK); Ireland (IE); Italy (IT); Japan (JP); Netherlands (NL); Norway (NO); Spain (ES); Switzerland (CH); United Kingdom (GB); United States (US).

**Table 3.14.** Factor loadings

Panel A: Trends in interconnectedness measures (VR) with fixed parameters							
Interconnectedness measures		Fixed betas/ Time-varying variances			Fixed variances/ Time-varying betas		
		Trend (%)	$t_{5\%}$	$t_{10\%}$	Trend (%)	$t_{5\%}$	$t_{10\%}$
Industry indices	Insurers	-0.6	(-1.0)	(-1.2)	1.7*	(1.4)	(2.3)
	Banks	-1.1	(-1.0)	(-1.4)	2.6*	(1.7)	(2.8)
	Average sector	0.9**	(-2.3)	(-3.0)	1.0**	(2.7)	(4.1)
Largest firms	Insurers	-0.0	(-0.1)	(-0.1)	1.7**	(5.0)	(5.9)
	Banks	-0.3	(-0.2)	(-0.3)	1.7**	(6.1)	(6.9)
	Average sector	0.6	(0.9)	(1.4)	0.6**	(7.1)	(7.8)

Panel B: Trend in betas							
Factor loadings		Industry indices			Largest firms		
		Trend (%)	$t_{5\%}$	$t_{10\%}$	Trend (%)	$t_{5\%}$	$t_{10\%}$
Global economic factor	Insurers	2.3**	(2.2)	(3.3)	2.2**	(3.3)	(4.2)
	Banks	2.7**	(2.4)	(3.5)	2.2**	(3.6)	(4.5)
	Average sector	1.7**	(3.3)	(4.5)	1.5**	(5.3)	(6.0)
Global industry factor	Insurers	1.6**	(4.2)	(5.4)	2.2**	(6.0)	(7.1)
	Banks	1.6**	(2.5)	(3.5)	2.0**	(2.5)	(3.5)
	Average sector	1.1**	(5.8)	(8.0)	1.1**	(3.8)	(5.4)
Regional economic factor	Insurers	1.4**	(4.7)	(5.5)	0.8**	(3.3)	(3.5)
	Banks	1.5**	(4.5)	(5.5)	0.2	(0.5)	(0.6)
	Average sector	0.6**	(4.2)	(5.0)	-0.3*	(1.8)	(2.1)
Regional industry factor	Insurers	1.4**	(14.1)	(15.8)	1.9**	(3.0)	(4.5)
	Banks	1.6**	(11.9)	(13.4)	1.2**	(4.5)	(5.3)
	Average sector	1.0*	(1.4)	(2.8)	0.6**	(2.4)	(3.7)
Local economic factor	Insurers	-0.3	(-0.4)	(-0.7)	-0.2	(-0.7)	(-0.8)
	Banks	0.0	(0.1)	(0.1)	0.3	(0.4)	(0.6)
	Average sector	-0.6	(-0.5)	(-1.2)	-0.5*	(1.4)	(2.1)

Panel C: Beta comparison								
Factor loadings	Insurance vs. Average sector				Insurance vs. Banking sector			
	Indices		Largest firms		Indices		Largest firms	
	Diff (%)	$t$ -stat	Diff (%)	$t$ -stat	Diff (%)	$t$ -stat	Diff (%)	$t$ -stat
Global economic factor	3.8***	(3.2)	21.6***	(13.1)	-11.3***	(-12.6)	3.0*	(2.0)
Global industry factor	-6.5***	(-5.1)	0.1	(0.0)	-16.3***	(-14.2)	-12.0***	(-7.1)
Regional economic factor	9.5***	(7.1)	17.9***	(10.6)	-2.2**	(-2.2)	7.6***	(5.8)
Regional industry factor	1.8**	(2.6)	10.3***	(6.3)	-10.7***	(-12.6)	2.3	(1.4)
Local economic factor	7.0***	(8.5)	8.1***	(6.8)	1.5*	(1.7)	3.1**	(2.4)

*Notes:* Panel A tests whether the increase in the interconnectedness measures (VR) is due to changes (i) in the variance of the series or (ii) in the factor loadings (see Equation 3.3). To this end, we recalculate VR by setting either betas or variances to their sample mean. In Panel B, we analyze the dynamics of the betas for insurers, banks, and non-financial firms. Trend tests are based on Bunnell and Vogelsang (2005). In Panel C, we compare the value of the factor loadings for insurers, banks, and non-financial firms based on paired t-tests. The spread (Diff) is expressed in percentage points. The signs \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively.

**Table 3.15.** Factor significance

Factors		Factor significance (t-value)		
		Sample period (1974–2018)	First sub-period (1974–1997)	Second sub-period (1997–2018)
Industry indices	Global economic factor	(6.4)***	(4.2)***	(8.7)***
	Global industry factor	(1.8)*	(0.9)	(2.6)***
	Regional economic factor	(4.5)***	(4.7)***	(4.4)***
	Regional industry factor	(1.7)*	(1.1)	(2.4)**
	Local economic factor	(5.6)***	(7.3)***	(3.9)***
Largest firms	Global economic factor	(4.1)***	(2.6)**	(5.6)***
	Global industry factor	(1.5)	(0.8)	(2.2)**
	Regional economic factor	(2.9)***	(3.2)***	(2.5)**
	Regional industry factor	(1.5)	(1.2)	(1.8)*
	Local economic factor	(4.1)***	(5.0)***	(3.2)***

*Notes:* This table displays the significance of the factor loadings estimated from the five-factor asset pricing model with time-varying parameters. The measures are based on the unweighted average of the t-values for our samples of industry indices and largest firms, respectively. We compute these measures for the entire sample period and analyze its evolution by dividing the sample into two equal sub-periods. The standard errors are robust to heteroscedasticity and autocorrelation (Newey and West, 1987). The signs \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively.

**Table 3.16.** Model comparison

Data/Residuals		Avg adj R <sup>2</sup> (%)	Avg abs(corr) (%)	Quant 25% (corr)	Quant 75% (corr)	CD-test	Exponent (%)
Local industry indices	Initial sample	n/a	41.4	22.9	35.7	1,652***	99.9
	Three-factor model	57.7	3.7	-1.5	2.4	31.2***	88.5
	Five-factor model	60.1	3.1	-1.5	1.9	7.9***	83.2
	Seven-factor model	60.3	3.1	-1.6	1.9	7.7***	83.5
Largest firms	Initial sample	n/a	26.7	13.4	23.5	764.0***	99.9
	Three-factor model	39.8	4.0	-1.7	2.4	30.2***	87.9
	Five-factor model	41.9	3.5	-1.5	2.0	24.2***	87.4
	Seven-factor model	42.7	3.5	-1.6	1.9	19.4***	86.4

*Notes:* This table tests the ability of various time-varying factor models to capture the degree of comovements across our sample. We compare the model performances based on several measures: (i) the average adjusted R-squared, (ii) the average of the absolute value of the pair-wise correlations, (iii) the 25 and 75% percentile pair-wise correlation coefficients, (iv) the test of weak cross-sectional dependence (H0) of Pesaran (2015), and (v) the exponent of cross-sectional relationship based on Bailey et al. (2016). A value between 0.5 and 1 implies a semi-strong to strong cross-sectional dependence. Since the global Fama–French factors are only available since 1990, the model comparison is limited to the period 1990–2018. The sign \*\*\* indicates significance at the 1% level.

# Conclusion

This thesis aims to improve the understanding of the long-term evolution of equity market comovements, which has become a central issue in the international finance literature. The dissertation consists of three chapters that attempt to answer the following questions:

- (i) Have stock market comovements increased over the past four decades, and can investors still benefit from international portfolio diversification?
- (ii) What are the determinants of the long-term evolution of stock market interdependencies?
- (iii) How has the interconnectedness of the insurance sector evolved over the past four decades compared to the other sectors of the economy?

These issues challenge business practices and policies for both investors and regulators.

We contribute to the literature in several ways. [Chapter 1](#) explores the influence of the choice of base assets on the long-term evolution of (i) stock market comovements and (ii) international diversification benefits (IDB). This analysis helps to explain some of the conflicting results in the existing literature. We also propose robust diversification measures that provide greater details on the sources of IDB's decline. Our main findings indicate that the correlation among country indices has significantly increased over time. By contrast, we find no such evidence for the correlation among local industry indices or individual securities. Based on our adjusted indicators, we show that the rise in the correlation among country indices partly stems from a decrease in domestic links between individual securities. This result highlights that the decline in IDB is not as severe as it might seem, as it partly stems from the rise in the

benefits of domestic diversification. Therefore, our outcomes help to explain why European investors remain significantly biased toward domestic assets (equity home bias).

Chapter 2 investigates the determinants of the long-term evolution of equity market interdependencies. By contrast, previous studies mostly examine the drivers of short-term changes in stock market comovements. Our approach is better suited to uncover the mechanisms behind the four-decade-rise in international stock return comovements. To this end, we use the dynamic panel models that handle non-stationary series, omitted factors, and feedback effects. In this chapter, we show that the determinants of the rise in stock market comovements are different in advanced and emerging market economies. Specifically, we reveal that the surge in interdependencies among advanced markets has been driven by increased trade openness. By contrast, increased comovements (i) among emerging markets and (ii) between developing and developed markets are the result of the purchase of domestic stocks by international investors. This is a significant issue for investors, as the rise in stock market interdependencies limits the benefits of international diversification. Consequently, the very search for investment opportunities in emerging markets seems to cause a decline in IDB. This result suggests the existence of an international diversification puzzle. Moreover, since foreign shareholders can theoretically transmit shocks across markets regardless of the fundamental links between countries, our findings indicate that part of the rise in emerging market interdependencies stems from non-fundamental investor-based linkages.

Chapter 3 focuses on three critical issues regarding the interconnectedness of insurers. We investigate: (i) whether the interdependencies of the insurance sector have structurally increased over the past four decades or only experienced a sudden rise during the global financial crisis (2007–2009); (ii) whether the risk of insurers' interconnectedness is concentrated in the largest insurance companies or spread over the entire insurance industry; (iii) whether the interconnectedness of banks and insurers present similar characteristics. These questions remain largely unanswered in the empirical literature. While existing papers mostly rely on systemic risk measures, we use a comovement indicator allowing us to analyze insurers' interconnectedness in the long run. This chapter shows a significant increase in insurers' interconnectedness with the rest of the financial sector and the real economy over the past four decades. Conversely, the interdependencies of non-financial firms have remained more stable over time. This up-

ward trend may be due to changes in insurers' business models and balance sheets. This finding supports the recent proposal of the IAIS to implement a new holistic macroprudential supervision. Also, we find that the major insurance companies are significantly more interdependent than the largest non-financial firms and the rest of the insurance sector. This result confirms that the risk of insurers' interconnectedness is mostly concentrated in the largest institutions and underscores the relevance of the entity-based macroprudential regulation initially implemented by the FSB. Finally, we show that insurers and banks are exposed to different sources of risk. While insurers are more vulnerable to macroeconomic and market shocks, banks have stronger links with the rest of the financial sector. This finding suggests that distinct regulatory measures may be needed to handle the features of banks and insurers' interconnections.

Our current work is penalized by certain limitations that could be addressed later. First, our empirical application in [Chapter 1](#) only focuses on 15 European stock markets. It would be interesting to apply the spread-based IDB measure to a broader set of countries to see whether our results can be extrapolated to the rest of the world. Besides, the use of adjusted correlation coefficients (e.g., [Forbes and Rigobon, 2002](#)) might help to improve further the robustness of the indicator to variations in non-diversifiable risks. Second, a shortfall of [Chapter 2](#) is that it cannot determine which type of investor-based channel is at the root of the rise in comovements among emerging markets. The same estimation method could be used with more specific data, disentangling between different types of investors, such as the equity holdings of index managers. Moreover, a new *de jure* measure of equity market openness available for many countries and over a long period would be beneficial to assess the advantages and drawbacks of stock market liberalization. Finally, [Chapter 3](#) could be extended by exploring the determinants of the long-term rise in insurers' interconnectedness. It would be interesting to check whether there is a long-term relationship between the increase in non-traditional activities and the rise in insurers' interconnectedness. However, insurers' balance sheet data are not readily available over long periods. Finally, the use of a global firm-level database could further enhance the robustness of our results.



## RÉSUMÉ

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Cette thèse étudie l'évolution de long terme et les principaux déterminants des comouvements entre les marchés actions. Ces questions sont importantes pour les investisseurs et les régulateurs, car les interdépendances entre les marchés boursiers (i) sont un élément clé des bénéfices de la diversification internationale des portefeuilles et (ii) peuvent affecter la stabilité financière en facilitant la propagation de chocs entre les pays.

Nos contributions à la littérature sont à la fois méthodologiques et empiriques. Nous développons des indicateurs qui apportent un nouvel éclairage sur l'évolution des bénéfices de la diversification internationale. Puis, nous étudions l'impact de long-terme de la globalisation sur l'augmentation des comouvements entre les marchés boursiers au cours des quatre dernières décennies. Enfin, nous examinons les interconnexions des compagnies d'assurance qui sont devenues un point central de la supervision macroprudentielle du secteur.

## MOTS CLÉS

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Comouvements, diversification internationale, interconnexions, marchés actions, mondialisation, secteur de l'assurance

## ABSTRACT

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This thesis studies the long-term evolution and the main determinants of international stock return comovements. These issues are of interest for investors and regulators, as stock market interdependencies (i) are a key element of the benefits of international portfolio diversification and (ii) can affect financial stability by facilitating the spread of shocks between countries.

Our contributions to the literature are both methodological and empirical. First, we develop diversification measures that shed new light on the evolution of international diversification benefits. Second, we study the long-term effect of globalization on the rise in international stock return comovements over the past four decades. Finally, we examine insurers' interconnectedness, which has become a key concern for the macroprudential supervision of the sector.

## KEYWORDS

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Comovements, globalization, interconnectedness, international diversification, insurance sector, stock markets