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Remember that you are one of the most privileged people on earth. Society has given you a wonderful opportunity. You are supposed to do whatever you want, to think about new ideas, to express your views freely, to do things in the way that you choose and on top you will be rewarded nicely. These privileges should not be taken for granted. We are extremely lucky – we owe something in return.

Ariel Rubinstein, 2011

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Contents

Chapter 1

Introduction

Financial crises are characterised by the sudden and simultaneous materialisation of risks that in tranquil times were believed to be independent. As a result, the opportunities for risk spreading are diminished when they are most needed, which can pose a substantial threat to the stability of the financial system. This effect was most recently illustrated by financial market developments since the course of 2007. What at first seemed to be a minor event in the US mortgage market, i.e. the default of a number of sub-prime mortgage loans, evolved into the largest financial crisis since the Great Depression of the 1930s. In this crisis, stock markets plummeted, risk premiums soared, money markets froze, financial institutions went bankrupt, and even national governments were on the brink of insolvency. While such events are rarely observed individually, they have now come together in what has become known as the Global Financial Crisis of 2007 and beyond.

The breakdown of risk spreading opportunities due to the simultaneous materialisation of risks has caused investors and policy makers to fear that financial instability spills over between markets or financial institutions as some sort of infectious disease, with one or more distressed markets or institutions causing otherwise healthy ones to become unstable as well. Borrowing a term from medicine, this phenomenon is referred to as contagion. Although the economic literature has not settled upon a precise definition of financial contagion (see Chapter 3 for a more elaborate discussion), policy makers and the public at large generally consider financial contagion to be the obvious culprit once parts of the financial system become unstable simultaneously.

Although both are often associated with one another, simultaneous instability of financial markets or institutions cannot by definition be attributed to financial contagion. After all, instead of instability of one market or institution *causing* the instability of another, both can also be unstable due to a third factor, which we will refer to as an adverse *common shock*. A natural example of a common shock is a sudden increase in global investor risk aversion, which would lead stock markets across the world to decline in value even when there are no economic linkages between them. Correlation of instability thus does not imply contagion. In the context of a financial crisis, the analogy with a domino effect springs to mind: the dominoes can fall together because one topples the other (contagion), or because a wind blow causes them to fall without the dominoes interacting with each other (common shock). Both effects have different implications for policy makers aiming to stabilise the financial system. If contagion is the main threat, stabilising one domino will also stabilise the others, while in the case of a common shock, the dominoes can only be stabilised by closing the open window.

The key difficulty to distinguish empirically between contagion and common shocks as causes for financial instability is that many common shocks cannot be observed directly. Empirical work on financial market contagion therefore generally starts by formulating a model of how these shocks could have evolved over time, and then attributes any correlation between markets that cannot be explained by this model to the impact of financial contagion. In their seminal contribution, King and Wadhwani (1990), for instance, assume that the intensity of common shocks is constant over time, and examine contagion by comparing correlation between markets during 'crisis' times with correlation during 'tranquil' times. Forbes and Rigobon (2002) however point out that the intensity of common shocks could increase during crisis times, which would drive up the correlation between markets as well. They propose to adjust the correlation statistic for this effect, but Corsetti, Pericoli, and Sbracia (2005) show that the way the correlation should be adjusted depends crucially on which particular model of common shocks the researcher has in mind. As there are as many preferred models as there are economists, the question of whether there is financial market contagion during crises remains heavily debated in the empirical literature.

The issue of how to control for common shocks carries over to the case where contagion between financial institutions is analysed. Especially banks are believed to be vulnerable to contagion, for instance because of their mutual exposures and their sensitivity to panic runs (De Bandt and Hartmann, 2002). Although empirical studies confirm that banks indeed tend to become unstable simultaneously, the 2007 Global Financial Crisis being a noteworthy example, several studies question whether this is really due to financial contagion. Calomiris and Mason (1997) compare attributes of failing and surviving banks during the Chicago panic of June 1932, and conclude that the failures reflect the relative weakness of banks in the face of a common asset value shock rather than contagion. Aharony and Swary (1983) find that large bank failures only affect other banks when caused by problems whose revelation is correlated across banks, but not when due to bank-specific factors such as internal fraud. More recently, Taylor (2009) and Huertas (2010) argue that even the near financial meltdown after the Lehman Brothers collapse on 15 September 2008 was not so much due to financial contagion, but was triggered by the common shock of investors' sudden doubts about the US government's willingness and ability to bail-out troubled financial institutions.

This thesis aims to add to the above literature by analysing to what extent simultaneous instability across financial markets or institutions is due to financial contagion, and to what extent it is due to adverse common shocks. This question, rather than the use of one single research method, binds the chapters of this thesis together. In fact, the adopted research methods are quite diverse, with the next chapter being theoretical in nature, and the other four being empirical.

Chapter 2 of this thesis focuses on the banking sector, where contagion during financial crises generally is believed to be omnipresent. Consequently, the banking sector is a particularly interesting candidate to highlight the potential importance of common shocks as alternative causes for financial instability. To this end, abstaining from any contagion effects, Chapter 2 asks the question what could be so special about banks that they are more sensitive than other firms to the type of adverse common shocks that can destabilise the sector as a whole? To provide an answer to this question, the chapter develops a theoretical model around one other characteristic of banks that makes them special compared to ordinary firms: their unique eligibility for liquidity assistance provided by the central banks in their role as Lenders of Last Resort.

It is well known that the Lender of Last Resort facility gives banks an incentive to engage in maturity transformation, i.e. to use short-term funds to finance their long-term loans. At the same time, the consensus is that "where liquidity support clearly can be separated from the provision of risk capital, the moral hazard created will be limited to possible mismanagement of liquidity risk" (Freixas, Giannini, Hoggarth and Soussa, 2000, p.73). However, Chapter 2 points out that through facilitating bank maturity transformation, the Lender of Last Resort facility effectively allows banks to save upon the spread between long-term and short-term interest rates when financing their activities. This borrowing cost advantage invalidates the assumption by Modigliani and Miller (1958) that firms borrow against the same interest rate as their shareholders. As a result, banks can create shareholder value by levering their balance sheets, i.e. by using more debt and less equity to finance their activities, as they can do this at a lower cost than their shareholders can lever their own portfolios. In addition, banks obtain an incentive to diversify, as this reduces the risk on banks' assets so that for any preferred level of default risk banks can increase their leverage further. Finally, competitive pressures cause banks to translate their lower borrowing costs into lower lending standards, which can lead them to finance investment projects of negative net present value and thereby inflate a credit bubble.

Chapter 2 shows that because of the liquidity insurance by the Lender of Last Resort, banks not only have an incentive to engage in excessive maturity transformation, but also to lever and diversify their balance sheets, and to lower their lending standards. This incentive causes banks' financing structures to become highly similar, with little equity and large amounts of short-term debt. In addition, diversification causes idiosyncratic risks in banks' asset portfolios to cancel out so that these portfolios become more correlated with the market portfolio, and therefore with each other (see also Allen and Jagtiani 2000, Wagner 2010a). Under such circumstances, banks are highly exposed to the same type of risks, and are thus likely to fail simultaneously. This vulnerability to common shocks provides a potentially important explanation for banks becoming unstable jointly.

Chapter 3 discusses the need to control for common shocks stemming from fluctuations in the currency of denomination when analysing contagion empirically. To this end, the chapter first summarises the main definitions of contagion adopted in the empirical literature, and then focuses on the analysis of stock market contagion. This strand of research can be seen as a branch from the early literature on diversification opportunities between international stock markets, e.g. Grubel (1968), with the contagion literature focusing on whether such opportunities still exist during crisis times. To examine this question, researchers generally analyse co-movements between stock market returns, but in many cases first convert these returns into US dollars. Doing so was appropriate in the early literature on stock market diversification, as exchange rate risk was difficult to hedge at the time so that focusing on US dollar returns was necessary to adopt the perspective of a US investor. Chapter 3 however shows that when analysing contagion, converting returns into a common currency can lead to biased results. By focusing on returns expressed in US dollars instead of in local currencies, fluctuations in the US dollar exchange rate effectively have the same impact as a common shock on the stock market returns under analysis, which leads to overestimation of contagion effects.

Chapter 4 empirically analyses contagion between financial markets by focusing on international stock market behaviour during the 1997 East Asian crisis and the 2007 Global Financial Crisis. A common approach to measure stock market contagion is to compare correlation between markets during 'tranquil' and 'crisis' periods, and investigate whether during the crisis period correlation is significantly elevated. This approach requires the researcher to correct any changes in the correlation for changes in the intensity of common shocks affecting the markets under scrutiny. Corsetti, Pericoli, and Sbracia (2005) show that as these shocks are unobserved, the outcomes of the analysis become crucially dependent on rather arbitrary assumptions regarding the behaviour of these shocks over time. Chapter 4 points out an additional cause for uncertainty associated with this type of analysis, namely the assumptions regarding the identification of the 'tranquil' and 'crisis' sample. The chapter analyses this issue by introducing a flexible measure of stock market synchronicity, which can be calculated for periods as short as a single trading day.

Identifying a 'crisis' sample boils down to selecting the combination of stock markets and trading days for which contagion is to be analysed. This choice is generally made ad hoc, with researchers first selecting a source market where any contagion effects are believed to have originated, and then examining contagion between this market and several other stock markets in the region. Also the trading days to be focused on are generally chosen on an ad-hoc basis. Broadly speaking two approaches exist: Forbes and Rigobon (2002) analyse a crisis period, using a fixed time-frame after a critical event such as the collapse of the Hong Kong stock market in 1997. Bae, Karolyi, and Stulz (2003) define a crisis quantile, focusing on a set of returns which are considered 'extreme' (e.g. those returns in the 5-percent lower tail of the distribution). We examine the robustness of both procedures by varying the choice of the 'crisis' sample through combining all possible source countries with all possible crisis periods or crisis quantiles. The analysis reveals that there are many arbitrary sub-samples for which synchronicity between stock markets is significantly higher than its full-sample value, suggesting that any increases in synchronicity during crisis times cannot necessarily be interpreted as evidence for contagion.

Chapter 5 analyses contagion between banks during the 2007 Global Financial Crisis. Fear of contagion was the main motive for the US government to rescue investment bank Bear Stearns and insurance company AIG, since the financial sector instability that could be triggered by these companies' bankruptcy was believed to be particularly large (see Bernanke 2008, Federal Reserve Board 2008). The failure of a bank can have a contagious impact on other banks through multiple channels, for instance by causing losses on bilateral exposures, by inducing write downs due to fire sales which depress market prices, or by triggering a loss of confidence amongst bank financiers. Even without the presence of unobserved common shocks these channels are hard to disentangle empirically.

To measure contagion between banks, Chapter 5 uses an identification strategy based on the presumption that if financial markets expect a bank's default to be contagious for any of the reasons outlined above, an increase in this bank's default probability should lead to a decline in other banks' market valuations. We put this hypothesis to the test by estimating a panel regression model where changes in banks' market values are driven by both an unobserved market factor and by changes in other banks' default probabilities. Contagion is thus not measured as residual co-movement between bank stock prices after controlling for common shocks, but is explicitly modeled as the impact of a change in one bank's default risk on another bank's market value. We estimate this model for a global sample of the one hundred largest banks during the 2007–2009 period, and find that banks' market values are to a large extent driven by common shocks as reflected by the market factor. The impact of changes in other banks' default probabilities is nearly negligible, also when we focus on contagion from larger banks or between banks which are more interconnected. This result suggests that the risk of contagion between banks is of minor importance compared to other factors driving banks' market values.

While the default of a single bank might induce little contagion effects after all, the default of entire countries could have a much larger destabilising impact on the financial system. Therefore, Chapter 6 focuses on developments in 2010, when the financial problems of Greece became so severe that the euro countries agreed to provide bilateral loans for a total amount of EUR 80 billion, with the International Monetary Fund in addition financing EUR 30 billion under a stand-by arrangement. European Central

Bank Vice-president Constâncio (2011) explains that fear of contagion was an important motivation to provide financial support to Greece, despite the no-bailout clause in the Maastricht Treaty. A restructuring of Greek debt could lead to a new banking crisis in the EU as several banks, notably in France and Germany, had a high exposure to Greece. In addition, a Greek default could spill over to other highly indebted countries in the euro area. The turmoil around the Greek debt crisis can however also be due to common shocks stemming from news about a potential bailout. As Cochrane (2010) puts it: "We're told that a Greek default will lead to 'contagion.' The only thing an investor learns about Portuguese, Spanish, and Italian finances from a Greek default is whether the EU will or won't bail them out too. Any 'contagion' here is entirely self-inflicted. If everyone knew there wouldn't be bailouts there would be no contagion."

To distinguish between contagion from a potential Greek default and the impact of news about a potential Greek bailout, Chapter 6 uses an event study approach as adopted by Aharony and Swary (1983). It identifies the events as the trading days in 2010 with the largest volatility in Greek government bond prices, and relates those days to the 'news' that caused these fluctuations. This approach circumvents a major problem of event studies, namely how to identify the main event days during which there is really an event that is not expected (and therefore already priced in). We relate the event dates either to news about Greek public finances or to news about the willingness of European countries to provide financial support to Greece. Using data for 48 European banks, we find that only news about the Greek bailout has a significant effect on bank stock prices, while news about Greek public finances does not have such an impact. Apparently, investors expect contagion from a potential Greek default to be small. However, we also find that the price of sovereign debt of Portugal, Ireland, and Spain responds to news about Greece's bailout as well as to news about Greece's public finances. This last finding could be interpreted as evidence for contagion, but is likely to be due to the so-called 'wake-up call' effect, where learning from news about a crisis country prompts investors to reassess the vulnerability of other countries as well.

Chapter 2

Common Shocks in the Banking Sector*

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* This chapter is based on Mink (2011).

2.1 Introduction

When different banks engage in the same types of risk-taking they become more sensitive to adverse shocks common to the sector as a whole, which can put at risk the stability of the financial system. The main types of risk-taking that are widely shared amongst banks are maturity transformation, leverage, diversification, and lending standard deterioration. By engaging in maturity transformation, banks finance long-term assets with short-term debt, which makes them prone to bank runs and sudden illiquidity.[1] By levering their balance sheets, banks use less equity to finance their assets, so that a small decline in asset value can cause them to become insolvent. Portfolio diversification in turn reduces banks' exposure to idiosyncratic risks, but increases their exposure to systematic risks so that they are more likely to become insolvent simultaneously.[2] Finally, by lowering their lending standards, banks can inflate a credit bubble, the bursting of which could trigger a financial crisis. Brunnermeier (2009) and Hellwig (2009) describe how this bank risk-taking intensified during the run-up to the 2007 financial crisis.

The 2007 financial crisis illustrates how the above four types of risk-taking are particularly prevalent in the banking sector, especially when contrasted with corporate risk-taking in sectors of the real economy. This chapter shows that at least to some extent, this risk-taking can be traced to a single institutional arrangement specific to the banking sector: the provision of illiquidity insurance by the Lender of Last Resort. We develop the mechanism through which the Lender of Last Resort affects bank risk-taking within a stripped-down modeling framework, abstracting from incomplete markets and asymmetric information that in more fully fledged models justify the role of banks as liquidity insurers and delegated monitors (see for instance Diamond and Dybvig 1983, Calomiris and Kahn 1991). An obvious limitation of this stylised approach is that we do not take into account the many additional incentives for banks to increase (or manage) their risk-taking, on which there is an extensive literature.[3]

[1] See for instance Diamond and Dybvig (1983) and Chen (1999).

[2] See for instance Allen and Jagtiani (2000), and Wagner (2008, 2010).

[3] Calomiris and Kahn (1991) and Diamond and Rajan (2001) explain that maturity transformation serves to discipline bank managers by increasing the risk of a bank-run. Furlong and Keeley (1987) explain banks' high leverage from the existence of retail deposit insurance, which for too-big-to-fail banks implicitly extends to wholesale creditors as well. Bank-specific diversification incentives are not typically discussed in the literature, but Penati and Protopapadakis (1988) argue that retail deposit insurance gives banks an incen-

Of course, on itself this does not invalidate the mechanism we highlight in our main analysis, which we believe can easily be incorporated in more fully fledged banking models.

The need for a Lender of Last Resort in managing financial crises has been widely acknowledged amongst both policy makers and academics, see for instance the review by Freixas, Giannini, Hoggarth, and Soussa (2000) and the references therein. In line with general insights from insurance economics, however, the provision of liquidity support causes moral hazard, with banks being stimulated to increase their liquidity risk-taking via maturity transformation.[4] Still, the consensus in the literature has been that "where liquidity support clearly can be separated from the provision of risk capital, the moral hazard created will be limited to possible mismanagement of liquidity risk" (Freixas, Giannini, Hoggarth and Soussa, 2000, p.73). This conclusion is confirmed by Repullo (2005), who shows that the Lender of Last Resort causes banks to increase illiquidity risk-taking while leaving the riskiness of their asset portfolio unchanged. If the Lender of Last Resort however reduces incentives for financiers to charge higher interest rates when banks are riskier, Repullo (2005) shows that banks choose riskier assets as well. In recent work by Farhi and Tirole (2012), banks can only increase maturity transformation via replacing equity by short-term debt, so that by stimulating maturity transformation, the Lender of Last Resort induces banks to increase their leverage as well.

We contribute to this literature by recognising that through facilitating bank maturity transformation, the Lender of Last Resort allows banks to borrow against short-term rather than long-term interest rates when financing their activities. Shareholders of banks do not have this advantage, as borrowing short-term to finance their invest-

tive to increase asset return correlation with each other deliberately, while Acharya and Yorulmazer (2007) and Farhi and Tirole (2012) attribute this incentive to implicit too-many-to-fail guarantees. Lending standard deterioration can be explained from short-sightedness or deteriorating ability of bank loan officers, see Rajan (1994) and Berger and Udell (2004).

[4] Liquidity support can be substantial especially when multiple banks are illiquid at the same time. During the current crisis for instance, central banks provided not only emergency liquidity support to individual banks, but also massively increased the supply of liquidity to the banking sector as a whole. ECB President Trichet (2009) explains that "the Eurosystem's open market operations have, in addition to steering short-term interest rates, also sought to ensure that solvent banks have continued access to liquidity. [...] We are now providing — and this is quite exceptional — unlimited refinancing to the banks of the euro area for maturities ranging from one week to six months in exchange for eligible collateral. [...] In total, the Eurosystem's balance sheet rose by about EUR 600 billion since end-June 2007 and today, an increase of about 65%."

ment portfolio one-on-one increases their illiquidity risk. As a result, banks can effectively borrow at a lower cost than their shareholders, so that bank leverage increases shareholder value. Bank diversification increases shareholder value by reducing the risk on banks' assets, so that for any target level of default risk banks can increase their leverage further. Competition between banks makes them translate their lower borrowing costs into lower lending standards, thereby financing investment projects of negative net present value.

In an extension to the model, we show that regulatory liquidity requirements aimed at limiting maturity transformation reduce all forms of bank risk-taking examined. Regulatory capital requirements are effective in reducing leverage and lending standard deterioration, but do not affect maturity transformation and diversification. In fact, if there are costs involved in diversifying into a new asset category, regulatory capital requirements increase diversification incentives by reducing the impact of these costs on banks' return on equity. Designing an optimal capital requirement then involves trading off the stability of individual banks against the stability of the banking sector as a whole. International capital requirements were already in place long before the outbreak of the 2007 Global Financial Crisis, while liquidity requirements will be incorporated in international banking regulation by 2018 (see Basel Committee on Banking Supervision 2010). Banks have opposed stricter capital and liquidity requirements by arguing that equity and long-term debt are both 'expensive' sources of funding. In our analysis this is also the case, but only because these funding sources do not allow banks to benefit from the illiquidity insurance by the Lender of Last Resort. As a result, as argued by Admati, DeMarzo, Hellwig, and Pfleiderer (2010), equity and long-term debt are not expensive from the perspective of society as a whole.[5]

Our model has two implications for further research. First, it suggests microeconomic bank risk-taking can be connected to the stance of the macro-economy via the difference between long-term and short-term interest rates. This term spread is a leading indicator of the business cycle (see also Ang, Piazzesi and Wei 2006 and the references therein), used for instance in the Conference Board's Leading Economic Index. Both bank profitability and bank risk-taking increase when the term spread steepens,

[5] See Van den Heuvel (2008) for a discussion of the welfare cost of bank capital requirements in a general equilibrium framework.

since engaging in maturity transformation then provides banks with a larger borrowing cost advantage. To the best of our knowledge this mechanism of procyclical bank risk-taking has not been established in the literature before. Bank risk-taking in turn could feed back into the term spread if maturity transformation and lending standard deterioration affect the (relative) price of long-term and short-term funds in the economy. Exploring both effects could shed further light on the interactions between the banking sector and the real economy, but is beyond the scope of the present chapter.

Second, our analysis suggests a relationship between bank risk-taking and monetary policy. First, lower policy rates translate into lower short-term interest rates and thus steepen the term spread directly. Second, when policy rates are low for a longer time, rising inflation expectations might drive up long-term interest rates and steepen the term spread further.[6] This relationship adds a new component to the 'risk-taking channel' of monetary policy discussed by Borio and Zhu (2008). Angeloni, Faia, and Lo Duca (2010) provide empirical evidence for the U.S. that lower policy rates increase bank leverage. Ioannidou, Ongena, and Peydró (2009), Jiménez, Ongena, Peydró, and Saurina (2010) and Maddaloni, Peydró, and Scopel (2010) document that lower policy rates weaken bank lending standards. The last authors also show that prolonging low policy rates weakens lending standards even further. These effects are suggested by our model as well.

The remainder of this chapter is organised as follows. Section 2.2 introduces a stylised model of bank risk-taking. Section 2.3 augments this model by introducing a Lender of Last Resort. Section 2.4 extends the model by analysing the effects of regulatory capital and liquidity requirements and by allowing for diversification costs. The final section concludes.

2.2 Risk-taking without illiquidity insurance

To facilitate interpreting the mechanism that drives banks to lever, diversify, and lower their lending standards, we use a simple model consisting of three components.

[6] Ellingsen and Söderström (2001) show that the impact of monetary policy on long-term interest rates is not unambiguous.

Lending projects. There are two long-term bank lending projects. Both projects are identical in the sense that for long-term risk-free interest rate $r > 0$, they yield returns with mean $(1+\pi)\,r$ and standard deviation σ (we omit project-specific subscripts for notational convenience). Banks charge the premium $\pi > 0$ as a compensation for the credit risk on their lending projects, so that $(1+\pi)\,r$ equals the cost effective interest rate given the riskiness of the projects. The two projects only differ in the sense that the correlation ρ between their returns is strictly smaller than 1, which provides banks with the opportunity to diversify.

Banks. There are two banks that both finance their assets A with debt D and equity E, so that for each bank $A = D + E$ with leverage $L = A/E$ (we omit bank-specific subscripts for notational convenience). The standard deviation of banks' equity returns is denoted by σ_E, with $\sigma_E = \sigma_A A/E$.[7] Banks can specialise in one lending project, or diversify by investing in both. When they diversify, the mean of the return on assets remains equal to $(1+\pi)\,r$, but the standard deviation thereof declines from σ to $\sqrt{0.5\,(1+\rho)}\sigma$.[8]

Shareholder. The shareholder has an amount I to invest in the equity of one or both banks, using borrowed funds B and own funds O so that $I = B + O$. In line with the above, the standard deviation of the return on the shareholder's own funds equals $\sigma_O = \sigma_I I/O$. The shareholder aims to maximise the return on his own funds given his preferred level of portfolio risk σ_O.[9]

As a benchmark case we assume that banks and the shareholder borrow against

[7] This expression follows from taking into account that the risk on assets is proportionally born by debt and equity holders according to $\sigma_A^2 = \sqrt{(E/A)^2\,\sigma_E^2 + (D/A)^2\,\sigma_D^2 + 2\,(E/A)\,(D/A)\,\mathrm{Cov}\,(\sigma_E\sigma_D)}$. We set the standard deviation of the return on debt σ_D equal to zero, which implies that the risk on assets is fully born by banks' equity holders. In practice this standard deviation is larger than zero since banks' debt holders suffer a loss if the bank would go bankrupt. During non-crisis times this effect is of little empirical importance, however, while taking it into account would complicate the model without qualitatively affecting its conclusions.

[8] Spreading funds evenly over both projects implies $\sigma_A = \sqrt{0.5^2\sigma^2 + 0.5^2\sigma^2 + 2\rho 0.5^2\sigma^2} = \sqrt{0.5\,(1+\rho)}\sigma$.

[9] The shareholder will accept a higher level of portfolio risk if this leads to a sufficiently higher portfolio return. We however assume the bank considers σ_O to be exogenous when it decides upon its actions, as in practice these actions only marginally affect the overall return on the broad portfolio of financial and non-financial assets owned by the shareholder. Moreover, allowing σ_O to increase in the return on own funds would leave the outcomes from the analysis qualitatively unaffected.

the risk-free interest rate r. The shareholder constructs a diversified portfolio as this reduces risk while keeping returns unchanged. He can do so in two ways: either by equally spreading his funds over two banks that each have specialised in a different lending project, or by buying shares of one bank that has equally spread his funds over both lending projects. The shareholder can also lever his portfolio in two ways. He can either lever himself by using borrowed funds to buy the shares of unlevered banks, or he can let the banks lever while using only his own funds to buy these banks' shares. We thus distinguish four alternative scenarios based on whether the bank or the shareholder levers and/or diversifies.

We show in the Appendix that under all four scenarios the shareholder's return on own funds (ROO) is the same, and equal to

$$ROO = \left(1 + \frac{\sigma_O}{\sigma} \frac{1}{\sqrt{0.5\,(1+\rho)}} \pi\right) r, \tag{2.1}$$

which can be written as $r + (A/O)\,\pi r$. This return can be interpreted as the shareholder's minimum *required* return, being equal to the interest rate on risk-free debt plus a cost effective reward required for the risk born on own funds (which increases in the cost-effective premium π and the total leverage of the bank and the shareholder A/O). As the shareholder's return on own funds is the same under all four scenarios, leverage and diversification at the bank level do not increase shareholder value. The reason is the same as in Modigliani and Miller (1958), being that the shareholder can also lever and diversify his portfolio himself. If we had allowed for (small) bankruptcy costs and economies of scale from banks lending to a single project, leverage and diversification at the level of the bank actually reduce shareholder value. Shareholder value also declines when banks lower their lending standards, which we show below can be modeled as banks charging interest rates below the cost effective level $(1+\pi)\,r$.

2.3 Risk-taking with illiquidity insurance

To analyse banks' incentive to lever, diversify, and lower their lending standards, we modify the set-up of the previous section by taking into account that banks obtain illiquidity insurance from the Lender of Last Resort. The Lender of Last Resort provides solvent banks with short-term funds when they are in imminent need of liquidity. Repullo (2005) models this insurance as central banks providing targeted loans to individual banks once outflows of short-term funds exceed their liquid assets available. Farhi and Tirole (2012) focus on a broader type of insurance, which goes beyond the traditional Lender of Last Resort definition, and have central banks lower monetary policy interest rates once banks suffer from illiquidity. Both types of insurance lead to moral hazard, which in the literature review by Freixas, Giannini, Hoggarth, and Soussa (2000) is summarised as banks increasing their illiquidity risk-taking. In the analysis by Repullo (2005), the higher illiquidity risk-taking manifests itself in the form of banks fully financed with short-term debt reducing their holdings of liquid short-term assets. In Farhi and Tirole (2012), the moral hazard is reflected by banks fully invested in illiquid long-term assets relying too much on short-term debt to finance their activities. As bank liquidity is a net concept relating available liquid assets to cash outflows, both effects are two sides of the same coin.

Financing long-term assets via rolling-over short-term debt, instead of issuing long-term debt, is generally referred to as maturity transformation. Also firms who do not benefit from a Lender of Last Resort can engage in maturity transformation, which has two opposite effects on their financing costs. First, financing costs decline as short-term risk-free interest rates are usually lower than long-term risk-free interest rates. Second, financing costs increase as debt holders charge (higher) credit risk premia on top of the risk-free interest rate and shareholders raise their required returns. This way, both equity and debt holders demand compensation for the risk that a sudden outflow of short-term funds could force the firm to prematurely liquidate assets, with insolvency as the potential outcome.

When modeling the impact of maturity transformation on bank financing costs, we take into account the existence of a Lender of Last Resort by assuming the second of the above two effects does not occur. This implies the Lender of Last Resort fully insures banks against illiquidity risk against a zero cost. While being a somewhat crude summary of the extensive literature on the Lender of Last Resort, this assumption greatly simplifies the analysis as it allows us to abstain from modeling any increases in credit risk premia on debt or in shareholders' required returns.[10] As a

[10] As risk premia on debt are an important mechanism through which bank financiers exercise market dis-

result, bank maturity transformation can be modeled simply by introducing a parameter $\tau > 0$, which indicates the amount of short-term debt as a fraction of total debt issued by the bank. In addition to the long-term interest rate r, we also define a short-term interest rate s, with the difference between both being equal to the term spread $r^* = r - s$. The average interest rate that banks pay on their issued debt is then given by $(1-\tau)\,r + \tau s = r - \tau r^*$.[11] As $\tau r^* > 0$, this average interest rate is lower than the long-term rate r, reflecting the first effect above that increasing maturity transformation lowers bank financing costs.

When banks engage in maturity transformation, both bank leverage and bank diversification affect shareholder value. To show this we again compare shareholders' return on own funds under the four scenarios discussed above. The scenarios where the shareholder levers (LS) yield a shareholder return on own funds equal to

$$ROO^{LS,DS} = ROO^{LS,DB} = \left(1 + \frac{\sigma_O}{\sigma}\frac{1}{\sqrt{0.5\,(1+\rho)}}\pi\right) r, \tag{2.2}$$

which does not depend on whether the shareholder diversifies (DS) or whether diversification is done by the bank (DB). Both returns on own funds are identical to the one in the previous section, since when the shareholder levers the ability of the bank to engage in maturity transformation is not put to use and thus does not affect the return on own funds. The returns on own funds change when the bank levers (LB) instead of the shareholder. When the bank levers and the shareholder diversifies, the shareholder's return on own funds equals

$$ROO^{LB,DS} = \left(1 + \frac{\sigma_O}{\sigma}\frac{1}{\sqrt{0.5\,(1+\rho)}}\pi\right) r + \left(\frac{\sigma_O}{\sigma} - 1\right)\frac{1}{\sqrt{0.5\,(1+\rho)}}\tau r^*, \tag{2.3}$$

cipline, abstaining from modeling them implies that our results do not do full justice to banks' incentives to adequately manage risks themselves.

[11] If we normalise the short-term interest rate s to equal zero, we have $r = r^*$ so that the average interest rate on bank debt becomes $(1-\tau)\,r$. This expression illustrates that in our framework the effect of maturity transformation on bank financing costs can be modeled in a way that is observationally equivalent to the modeling of the corporate debt tax shield discussed by Modigliani and Miller (1958), where the parameter τ indicates the corporate income tax rate. The risk-taking mechanism in our model is therefore closely related to the insights of Modigliani and Miller (1958) and Lewellen (1971) that the debt tax shield provides firms with an incentive to increase leverage and diversification.

while when instead the bank diversifies this return becomes

$$\begin{aligned} ROO^{LB,DB} &= \left(1+\frac{\sigma_O}{\sigma}\frac{1}{\sqrt{0.5\,(1+\rho)}}\pi\right) r + \left(\frac{\sigma_O}{\sigma}-1\right)\frac{1}{\sqrt{0.5\,(1+\rho)}}\tau r^* \\ &+ \left(\frac{1}{\sqrt{0.5\,(1+\rho)}}-1\right)\tau r^*. \end{aligned} \tag{2.4}$$

This last expression can be written as $r + (A/O)\,\pi r + (A/O-1)\,\tau r^*$, which is equal to the risk-free long-term interest rate plus a reward required for the risk born on own funds, and plus the additional profits from engaging in maturity transformation τ. When $\tau > 0$, the last term of this expression is larger than zero, so that engaging in maturity transformation increases shareholder value through raising the return on own funds (while leaving required returns unchanged at $r + (A/O)\,\pi r$). The expression for this return on own funds implies bank profitability increases in the term spread r^*, which is a well known empirical regularity. We discuss below what the composition of this return on own funds implies for the impact of leverage, diversification, and lending standard deterioration on shareholder value.

2.3.1 Bank leverage and shareholder value

Comparing the returns on own funds in Equations (2.2) and (2.3) shows that the gain for the shareholder from letting the bank lever instead of doing so himself can be written as

$$ROO^{LS,DS} - ROO^{LB,DS} = \left(\frac{\sigma_O}{\sigma}-1\right)\frac{1}{\sqrt{0.5\,(1+\rho)}}\tau r^*. \tag{2.5}$$

Since this gain is always positive when $\sigma_O/\sigma > 1$, letting the bank borrow instead of the shareholder always increases shareholder value. The intuition behind this result is that because of its ability to roll-over short-term debt without running illiquidity risk, the bank can effectively finance its assets against a lower interest rate than the shareholder. The shareholder therefore receives a higher return on own funds when he lets the bank borrow instead of doing so himself. Going from left to right in Equation (2.5), the incentive for the bank to lever instead of the shareholder is stronger when:

Shareholders prefer more risk. When σ_O is higher, shareholders prefer a more risky investment portfolio, and thus want to take a more leveraged exposure to the projects that banks invest in. This requires a larger amount of debt to be issued, which increases the gain from letting the bank doing so and exploit its borrowing cost advantage.

Banks invest in safer projects. When σ is lower, banks invest in less risky projects. For a given level of shareholder risk preference this allows for a larger amount of debt to be issued, which increases the gain from letting the bank doing so to exploit its borrowing cost advantage.

Lending projects are less correlated. When the correlation ρ between lending projects is lower, this leads to a smaller value of $\sqrt{0.5\,(1+\rho)}$. For a given level of riskiness of these individual lending projects, the risk on the shareholder's own funds is then lower. Shareholders therefore need more leverage to align their portfolio's risk with their personal risk preferences, which increases the benefits from letting the bank borrow instead of doing so themselves.

Bank maturity transformation is higher. When τ is higher, banks finance themselves with a larger proportion of short-term funds, which increases the borrowing cost advantage they have over their shareholders. Shareholders are then more likely to prefer the bank to lever rather than doing so themselves.

The term spread is steeper. When r^* is higher, the term spread is steeper so that the difference between long-term and short-term interest rates is larger. The borrowing cost advantage stemming from banks' ability to engage in maturity transformation is then larger, so that bank instead of shareholder leverage becomes more attractive.

2.3.2 Bank diversification and shareholder value

If banks did not lever they also would not have an incentive to diversify, as follows directly from Equation (2.2). Having established however that bank shareholders gain from letting banks lever, banks obtain an incentive to diversify as well. The intuition behind this result is that bank leverage $L = A/E$ is related to the bank's standard deviation of equity according to $L\sigma_A = \sigma_E$, as was shown in Section 2.2. As a result, using diversification to reduce the risk on its lending portfolio allows the bank to increase leverage without having to increase its default risk (which increases in σ_E). Comparing Equations (2.3) and (2.4) shows that bank diversification increases shareholders' return on own funds by

$$ROO^{LB,DS} - ROO^{LB,DB} = \left(\frac{1}{\sqrt{0.5\,(1+\rho)}} - 1 \right) \tau r^*, \tag{2.6}$$

which is always larger than zero. Going from left to right in Equation (2.6), the shareholder's gain from letting the bank diversify instead of doing so himself is larger when:

Lending projects are less correlated. When the correlation ρ between lending projects is lower, the value of $\sqrt{0.5\,(1+\rho)}$ decreases. Diversifying between lending projects then leads to a larger reduction in the risk on assets, and thus creates more room for bank leverage to exploit the bank's borrowing cost advantage.

Bank maturity transformation is higher. When τ is higher, banks finance themselves with a larger proportion of short-term funds, which increases their borrowing cost advantage relative to their shareholders. Banks' incentive to diversify then increases, as doing so allows for more exploitation of this borrowing cost advantage.

The term spread is steeper. When r^* is higher, the term spread is steeper so that the difference between long-term and short-term interest rates is larger. The borrowing cost advantage stemming from banks' ability to engage in maturity transformation is then larger, so that bank instead of shareholder leverage becomes more attractive. In turn, this increases the gain from bank diversification as well.

2.3.3 Bank lending standard deterioration and shareholder value

Up to this point we have allowed the gains from bank maturity transformation to fully accrue to the shareholder in the form of a higher return on his own funds. This is however not necessarily the case, since in a competitive bank lending market, banks will also use these gains to lower the price of their loans. To allow for this effect we model bank lending rates as $(1 + \pi - \delta)\, r$, where $\delta > 0$ is a discount offered by the bank on the original cost effective loan rate. The corresponding return on own funds when the bank levers and diversifies is obtained by replacing π in Equation (2.4) by $(\pi - \delta)$. Naturally, the bank can only offer a discount as long as the shareholder's return on own funds at least remains equal to his required return reported in Equation (2.2). As a result, the discount that the bank can offer is constrained by

$$\delta < \left(1 - \frac{\sigma}{\sigma_O}\sqrt{0.5\,(1+\rho)}\right)\tau\left(1 - \frac{s}{r}\right), \tag{2.7}$$

which can be written as $\delta < \left(1 - 1/L^{LB,DB}\right)\tau\,(r^*/r)$.[12] The right hand side of this condition is larger than zero, indicating that by engaging in maturity transformation, the bank can offer a non-zero discount on the original lending rate. Going from left to right in Equation (2.7), this discount increases when:

Shareholders prefer more risk. When σ_O is higher, shareholders prefer a more risky investment portfolio, and thus want to take a more leveraged exposure to the projects that banks invest in. This allows banks to use more debt to finance their lending projects, which increases the gains from maturity transformation and allows for lower bank lending rates.

Banks invest in safer projects. When σ is lower, banks invest in less risky projects. They can then use more leverage to finance these projects, and thus obtain a larger gain from their ability to engage in maturity transformation. As a result, they can give a larger discount on their lending rates.

Lending projects are less correlated. When the correlation ρ between lending projects is lower, the value of $\sqrt{0.5\,(1+\rho)}$ decreases. Diversifying between lending projects then leads to a larger reduction in the risk on assets. This again allows for more leverage and a larger gain from maturity transformation, so that bank lending rates can be

[12] This result follows from noticing that when the bank levers and the shareholder does not, $\sigma_O = \sigma_E$ so that $\sigma_O/\sqrt{0.5\,(1+\rho)}\sigma = L^{LB,DB}$.

lower.

Bank maturity transformation is higher. When τ is higher, banks finance themselves with a larger proportion of short-term funds, which lowers their borrowing costs so that lending rates can be lower as well.

The term spread is steeper. When s/r is smaller, short-term interest rates are lower and the difference between long-term and short-term interest rates is larger, so that the term spread is steeper. The borrowing cost advantage stemming from banks' ability to engage in maturity transformation is then larger, so that it can offer a larger discount on its lending rates.

By offering a discount, banks charge lending rates below the cost effective level $(1+\pi)\,r$. Equation (2.7) even implies that if maturity transformation and leverage are high enough, the discount δ can be larger than the risk-premium π. Banks then lend against rates below the risk-free level r. As any non-zero discount δ implies that banks finance lending projects of negative net present value, offering such a discount implies that lending standards deteriorate.[13] This deterioration in lending standards can also be illustrated by realising that, instead of charging lower lending rates for the original lending projects, banks can use the additional profits from maturity transformation to finance riskier lending projects against the original interest rates $(1+\pi)\,r$. Both cases are two sides of the same coin, and imply an expansion of credit supply into assets that are too risky for the returns they generate.

[13] The result that the projects' NPV is negative follows from noticing that the bank invests an amount A in a project that yields a return of $(1+\pi-\delta)\,r$, while given the project's riskiness the return required equals $(1+\pi)\,r$. The net present value of the project is then equal to $-\frac{A}{1}+\frac{A}{1+(1+\pi)r}+\frac{(1+\pi-\delta)rA}{1+(1+\pi)r}=-\frac{\delta}{1+\pi+1/r}$, which is smaller then zero.

2.4 Extensions

2.4.1 Regulatory capital and liquidity requirements

To reduce bank risk-taking, bank regulators impose capital buffer requirements. In particular, regulators limit the ratio of banks' risk-weighted assets over their equity buffers. In our model this ratio is equal to $\sigma_A A/E = \sigma_E$, so that capital requirements can be modeled as regulators imposing an upper limit $\bar{\sigma}_E < \sigma_O$ on the standard deviation of banks' equity. As a result bank leverage declines from σ_O/σ to $\bar{\sigma}_E/\sigma$. Replacing σ_O in Equation (2.5) by $\bar{\sigma}_E$ shows that regulatory capital requirements limit shareholder gains from bank leverage, while doing the same in Equation (2.7) shows that they limit lending standard deterioration as well. Bank capital requirements however do not limit the incentive to diversify, since σ_O does not enter Equation (2.6). The intuition behind this result is that the percentage decline in the capital requirement that can be achieved through diversification is independent of the size of this requirement itself.

In addition to imposing capital buffer requirements, the international banking regulation reforms set in motion since the 2007 Global Financial Crisis allow regulators to impose bank liquidity buffer requirements as well (see Basel Committee on Banking Supervision 2010). These requirements work to limit the maturity mismatch between banks' assets and liabilities, and can be modeled as regulators imposing an upper limit $\bar{\tau}$ on the amount of bank maturity transformation. Replacing τ by $\bar{\tau}$ in Equations (2.5)–(2.7) shows that such a limit would also reduce the gains from leverage and diversification, and would in addition reduce banks' ability to offer a discount on their lending rates.

In addition to reducing bank risk-taking, capital and liquidity requirements lead bank profits to be lower and cause bank loans to become more expensive. After all, in the extreme case where $\bar{\sigma}_E = \sigma_A$ and/or $\bar{\tau} = 0$, banks cannot afford to offer a discount on their lending rates anymore, while to the extent that they used to pass on the gains from maturity transformation to their shareholders, profits will be lower as well. These effects are counterbalanced by a decline in the illiquidity insurance provided by the Lender of Last Resort. As a result, banks will consider equity and long-term debt to be expensive sources of funding, but both are not expensive funding sources from the perspective of society as a whole (see also Admati, DeMarzo, Hellwig, and Pfleiderer 2010).

2.4.2 Diversification costs

The previous analysis assumes that banks can diversify at a zero cost. In practice, however, there are expenses involved when banks decide to invest part of their assets in an additional project, for instance because they have to set up an office network in another geographical region or need to acquire knowledge about a new product market. We model these expenses as banks having to pay a fixed cost C in addition to their interest expenses when they choose to diversify. In this case, the gain from diversification in Equation (2.6) must be augmented by a term $-C/O$. When there is a regulatory capital requirement, this gain can be written as

$$ROO^{LB,DS} - ROO^{LB,DB} = \left(\frac{1}{\sqrt{0.5\,(1+\rho)}} - 1 \right) \tau r^{*} - \frac{C}{A} \bar{L}^{LB,DB}, \tag{2.8}$$

with $\bar{L}$ denoting the leverage limit implied by the capital requirement $\bar{\sigma}_E$.

The last term in the above expression has three implications. First, diversification obviously becomes more attractive when the diversification cost C declines. Such a decline could be due to ongoing financial innovation making more risks tradeable, with for instance the ability to buy securitised assets having allowed banks from all over the world to issue U.S. mortgage loans without having to establish a local office network. Second, diversification becomes more attractive when bank size A is larger, since this reduces a bank's relative burden of paying the fixed cost C. Large banks are thus more likely to diversify, in line with the intuition that large banks tend to be globally diversified while small banks tend to focus on local niche markets. Finally, diversification becomes more attractive when capital requirements $\bar{L}$ are stricter, as the cost C is then smaller relative to banks' equity buffers and thus has a smaller impact on their return on equity. While micro-prudential capital requirements reduce the probability that an individual bank defaults, through stimulating diversification they can thus increase the probability that such a default coincides with those of the other bank(s). Designing an optimal capital requirement then requires trading off the stability of individual banks against the stability of the banking sector as a whole.[14]

2.5 Conclusion

Excessive bank maturity transformation, leverage, diversification, and lending standard deterioration can put the stability of the financial system at risk. This effect was illustrated by the outbreak of the 2007 Global Financial Crisis, which has drawn renewed attention to the question of why especially banks engage in these forms of risk-taking. We analyse this question by outlining a mechanism in which providing banks with illiquidity insurance through a Lender of Last Resort is sufficient to give them an incentive to engage in maturity transformation, leverage, diversification, and lending standard deterioration. Naturally, when all banks engage in these same forms of risk-taking, this makes them more sensitive to adverse common shocks.

In our model, the moral hazard from Lender of Last Resort interventions can effectively be reduced via regulatory bank liquidity requirements. Regulatory capital requirements reduce the probability of individual bank defaults, but can stimulate bank diversification and thereby increase the probability that such defaults occur simultaneously. While banks consider equity and long-term debt to be expensive sources of funding, in our model both are not expensive from the perspective of society as a whole.

The model connects both micro-economic bank profitability and risk-taking to the overall stance of the macro-economy via the term spread, which is a well-known indicator of the business cycle. Bank risk-taking is suggested to be procyclical as it becomes more profitable when the term spread steepens. The analysis also suggests a new risk-taking channel of monetary policy, as lower policy rates can steepen the term spread and thereby increase bank risk-taking. Although we have adopted a stylised modeling framework to establish our results, analysing these mechanisms in more detail within the context of a general equilibrium model is a fruitful area for future research.

[14] Zhou (2010) arrives at the same conclusion, although his risk-taking mechanism differs from the one outlined above.

2.A Appendix

If the shareholder levers (LS) instead of the bank, the bank's equity is by definition equal to the bank's assets. In the scenario where the shareholder diversifies (DS) and chooses the bank to specialise, this implies that $E^{LS,DS} = A$. The bank's return on equity (ROE) then equals the income from investing in a single project divided by total shareholder equity:

$$\begin{aligned} ROE^{LS,DS} &= \frac{(1+\pi)\, rA}{E^{LS,DS}} \\ &= \frac{A}{A}(1+\pi)\, r \\ &= \pi r + r. \end{aligned}$$

The shareholder now equally spreads his funds over the shares of two specialised banks. His return on own funds (ROO) then equals the return on the investment in both banks' equity minus his interest expenditure on borrowed funds, divided by his amount of own funds:

$$\begin{aligned} ROO^{LS,DS} &= \frac{ROE^{LS,DS} I^{LS,DS} - r\left(I^{LS,DS} - O\right)}{O} \\ &= \frac{I^{LS,DS}}{O}\left(ROE^{LS,DS} - r\right) + r \\ &= \frac{\sigma_O}{\sigma}\frac{1}{\sqrt{0.5\,(1+\rho)}}\pi r + r, \end{aligned}$$

where for the last step we use $I^{LS,DS}/O = \sigma_O/\sigma_I^{LS,DS} = \sigma_O/\sqrt{0.5\,(1+\rho)}\sigma$. This result follows from the fact that as the bank does not lever, the standard deviation of his equity is equal to the standard deviation of his assets. Hence, when the shareholder spreads his investment equally over both banks' equity, the standard deviation of the resulting investment portfolio equals $\sigma_I^{LS,DS} = \sqrt{0.5^2\sigma^2 + 0.5^2\sigma^2 + 2\rho 0.5^2\sigma^2} = \sqrt{0.5\,(1+\rho)}\sigma$.

In the scenario where the shareholder levers and the bank diversifies (DB) by investing in both projects, the bank's return on equity equals

$$ROE^{LS,DB} = \frac{(1+\pi)\, rA}{E^{LS,DB}}$$

$$\begin{aligned} &= \frac{A}{A}(1+\pi)r \\ &= \pi r + r. \end{aligned}$$

The shareholder now invests all his funds in the diversified bank's equity, in which case he earns a return on own funds equal to

$$\begin{aligned} ROO^{LS,DB} &= \frac{ROE^{LS,DB} I^{LS,DB} - r\left(I^{LS,DB} - O\right)}{O} \\ &= \frac{I^{LS,DB}}{O}\left(ROE^{LS,DB} - r\right) + r \\ &= \frac{\sigma_O}{\sigma}\frac{1}{\sqrt{0.5(1+\rho)}}\pi r + r, \end{aligned}$$

where for the last step we use $I^{LS,DB}/O = \sigma_O/\sigma_I^{LS,DB} = \sigma_O/\sqrt{0.5(1+\rho)}\sigma$.

Instead of levering his investment portfolio himself, the shareholder can also let the bank lever (LB). The shareholder then does not borrow himself, but only uses his own funds to buy banks' equity. As a result, the amount of shareholder own funds is by definition equal to the amount of shareholder investments. In the scenario where the shareholder diversifies and lets the bank specialise in a single lending project, this implies that $O = I^{LB,DS}$ in which case the bank's return on equity equals

$$\begin{aligned} ROE^{LB,DS} &= \frac{(1+\pi)rA - r\left(A - E^{LB,DS}\right)}{E^{LB,DS}} \\ &= \frac{A}{E^{LB,DS}}\pi r + r \\ &= \frac{\sigma_O}{\sigma}\frac{1}{\sqrt{0.5(1+\rho)}}\pi r + r, \end{aligned}$$

where in the last step we use $A/E^{LB,DS} = \sigma_E^{LB,DS}/\sigma = \sigma_O/\sqrt{0.5(1+\rho)}\sigma$. This result follows from the fact that when the shareholder does not lever, the standard deviation of his own funds equals the standard deviation of his investment portfolio, so that $\sigma_O = \sigma_I^{LB,DS} = \sqrt{0.5(1+\rho)}\sigma_E^{LB,DS}$. When the shareholder now spreads his funds over two specialised banks, his return on own funds equals

$$ROO^{LB,DS} = \frac{ROE^{LB,DS} I^{LB,DS}}{O}$$

$$
\begin{aligned}
&= \frac{O}{O} ROE^{LB,DS} \\
&= \frac{\sigma_O}{\sigma} \frac{1}{\sqrt{0.5\,(1+\rho)}} \pi r + r.
\end{aligned}
$$

Finally, in the last scenario the bank both levers and diversifies instead of the shareholder, so that its return on equity equals

$$
\begin{aligned}
ROE^{LB,DB} &= \frac{(1+\pi)\, rA - r\left(A - E^{LB,DB}\right)}{E^{LB,DB}} \\
&= \frac{A}{E^{LB,DB}} \pi r + r \\
&= \frac{\sigma_O}{\sigma} \frac{1}{\sqrt{0.5\,(1+\rho)}} \pi r + r,
\end{aligned}
$$

where in the last step we use $A/E^{LB,DS} = \sigma_E^{LB,DS}/\sigma = \sigma_O/\sqrt{0.5\,(1+\rho)}\sigma$. The return on own funds for the shareholder who invests in the levered diversified bank then equals

$$
\begin{aligned}
ROO^{LB,DB} &= \frac{ROE^{LB,DB} I^{LB,DB}}{O} \\
&= \frac{O}{O} ROE^{LB,DB} \\
&= \frac{\sigma_O}{\sigma} \frac{1}{\sqrt{0.5\,(1+\rho)}} \pi r + r.
\end{aligned}
$$

Chapter 3

Common Shocks in Common Currency Returns*

* This chapter is based on Mink (2009).

3.1 Introduction

While there exist various definitions of financial contagion, which we discuss below, empirical research generally focuses on the co-movement between contemporaneous market returns, for instance using a measure of correlation between them. As a first step in analysing these similarities, the original local currency returns are often converted into a common currency, for which usually the US dollar is chosen. The motivation for this choice, if any is provided, is generally that converting returns into US dollars is consistent with 'the perspective of an international investor'. This chapter shows that such conversion is at odds with the literature on contagious shock transmission, and can bias empirical findings when for instance analysing the Global Financial Crisis of 2007–2010. The reason for this bias is that when analysing returns expressed in a common currency, fluctuations in this currency's exchange rate effectively act as a common shock driving the observed stock market returns. These exchange rate fluctuations can then create the impression of stock market contagion when in reality there is none.

The remainder of this Chapter is organised as follows. Section 3.2 summarises the main definitions of contagion adopted in the empirical literature. Section 3.3 discusses why this literature focuses on market returns converted to a common currency, and explains why local currency returns are better used instead. Section 3.4 empirically illustrates the bias that arises when focusing on US dollar returns. The final section concludes.

3.2 Defining contagion

The empirical literature uses various definitions of financial contagion, see for instance the overviews by Rigobon (2002) and Pericoli and Sbracia (2003). Still, most commonly used definitions of financial contagion can be traced to a few influential papers, and, as Dungey, Fry, Gonzales-Hermosillo, and Martin (2005) show, share several similarities. Below, we discuss the most influential definitions, which mainly differ with respect to when contagion is believed to potentially take place: always, or only during a financial crisis?

The seminal work by Forbes and Rigobon (2002) defines contagion between financial markets as a significant increase in cross-market linkages after a shock to one country. If there is no such significant increase, but instead there are strong linkages between the two economies that exist in all states of the world, the authors refer to this as interdependence between markets. Contagion thus only occurs during a financial crisis, defined as an adjacent time period (e.g. one month) after some exogenously identified crisis event. This event can be the crash of a national stock market index, or, as for instance in Chapter 4, the collapse of Lehman Brothers on 15 September 2008.

Bae, Karolyi, and Stulz (2003) analyse contagion by focusing on days with extreme stock market returns, or so-called exceedance events. The authors define contagion as the fraction of the exceedance events in a particular region that is left unexplained by its own covariates but that is explained by the exceedances from another region. When exceedances occur simultaneously across financial markets, Bae, Karolyi, and Stulz (2003) refer to this as a co-exceedance event. Parallel to the approach by Forbes and Rigobon (2002), contagion thus only occurs during times of crises. These times however do not comprise a certain period following a crisis event, but cover the set of trading days during which returns exceed an exogenously identified threshold value. Bae, Karolyi, and Stulz (2003) focus on the 5 percent most extreme returns in the distribution, while Chapter 4 examines contagion using other threshold values as well.

Bekaert, Harvey, and Ng (2005) use a contagion definition that differs from the two above, because they argue that contagion between financial markets implies that there is correlation over and above what one would expect from economic fundamentals. This definition allows contagion to occur during the full sample period rather than being specifically associated with crisis times. At the same time, it requires the researcher to explicitly formulate a model of fundamental transmission between markets. To this end, Bekaert, Harvey, and Ng (2005) adopt a CAPM-style factor model with time varying beta coefficients, and measure contagion as the correlation between the model's residuals.

Finally, Aharony and Swary (1983) focus on contagion between banks, which they define as a domino-effect where regardless of the cause of bank failure, its effects spill over to other banks, too. This definition implies contagion is associated with particular crisis events, i.e. bank failures. The authors use an event study to examine the impact of large bank defaults on other banks. Chapter 5 explains that anticipation by market participants of such failure events can give rise to contagion also when the actual default eventually does not occur. Chapter 6 shows that the definition by Aharony and Swary (1983) can be applied to contagion from sovereign defaults as well.

In their review of the literature, De Bandt and Hartmann (2002) summarise the various definitions of contagion as the situation where the release of bad news about a financial institution, or even its failure, or the crash of a financial market leads in a sequential fashion to considerable adverse effects on one or several other financial institutions or markets. These adverse effects have to be such that the institutions affected in the second round or later actually fail as a consequence of the initial shock, although they have been fundamentally solvent ex ante, or that the market(s) affected in later rounds also crash and would not have done so without the initial shock. According to this definition, contagion is associated with large adverse events and does not occur during normal times.

A commonality shared by the above approaches is that contagion is measured as a residual. That is, contagion is analysed by focusing on the residuals of a model of 'fundamental' asset returns, including any common shocks. These fundamentals can be modeled either explicitly, as in Bekaert, Harvey, and Ng (2005), or implicitly as in Forbes and Rigobon (2002). Consequently, as pointed out by Corsetti, Pericoli, and Sbracia (2005), the results from the analysis are conditional upon how the researcher chooses to model these fundamental factors. As many of these factors cannot be observed directly, a popular approach is to resort to time series modeling techniques and for instance specify the factors as GARCH processes (see Dungey, Fry, Gonzales-Hermosillo, and Martin 2005). Chapter 5 adopts an alternative approach, and models contagion as the coefficient estimate obtained when regressing changes in one bank's market value on changes in another bank's default risk.

For the purpose of the present thesis and the analysis below, the main message from this overview is that all contagion definitions are consistent with the idea that contagion is something different than a common shock. As explained in the first chapter, this distinction is relevant from both an academic and a policy perspective.

3.3 Common versus local currency returns

In many cases researchers measure contagion between markets after first converting the local currency returns into US dollars. The relationship between stock market returns converted to US dollars and stock market returns expressed in local currencies reads

$$R_{i,t}^{\$} = \ln\left(P_{i,t}/P_{i,t-1}\right) + \ln\left(E_{i,t}^{\$}/E_{i,t-1}^{\$}\right), \tag{3.1}$$

where P_i is the price index of country i's stock market, and $E_i^{\$}$ is the exchange rate expressed as US dollars per domestic currency of country i. The stock market return in US dollars, $R_{i,t}^{\$}$, can thus be decomposed in the local currency stock market return, $\ln\left(P_{i,t}/P_{i,t-1}\right)$, and the change in the dollar exchange rate, $\ln\left(E_{i,t}^{\$}/E_{i,t-1}^{\$}\right)$.

While local currency stock market returns and exchange rate fluctuations can be distinguished in theory, they were not always separable in practice. To appreciate this point we have to go back to earlier work on diversification between stock markets by for instance Grubel (1968). At the time, exchange rate risk was difficult to hedge so that domestic investors could not invest in foreign stock markets without exposing themselves to exchange rate fluctuations. The potential gains from international portfolio diversification were therefore different for an American investor than for a British investor, say, since both investors were exposed to fluctuations in different exchange rates when converting their international portfolios' returns into their domestic currencies. When Grubel (1968) calculated the correlation between US and foreign stock market returns, he therefore focused on returns in US dollars since he aimed "to demonstrate the range of possible gains to *American* investors from international diversification of their portfolios" (p. 1304, italics added). In a similar diversification study using US dollar returns, Levy and Sarnat (1970) note that this conversion implies that "the optimal investment proportions set out in this paper are relevant ... for [investors from] the United States, but not for [investors from] the United Kingdom" (p. 669).

As the literature on international portfolio diversification evolved, a natural extension was to analyse whether the correlation between international stock markets changed over time (see for instance Kaplanis, 1988). The October 1987 crash of the US stock market and the simultaneous declines in other major stock markets caused the literature to redirect focus to changes in correlation coefficients during times of crisis, fearing that in such times 'all correlations tend to one'. This inspired the strand of research that by now has become part of the empirical literature on contagion. Table 3.1 shows that most empirical contributions in this field follow the original diversification literature in focusing (also) on US dollar returns, without providing much motivation for this choice. At best, authors briefly refer to 'common practice' or to the aforementioned 'perspective of the international investor'. While converting returns to a common currency was appropriate to analyse diversification gains when exchange rate risk was difficult to hedge, such conversion is inappropriate when analysing contagion between stock markets.

When analysing contagion between stock markets, adopting a particular investor perspective by converting returns to a common currency is not a trivial issue. For instance, what to do when one finds empirical evidence for contagion between market returns converted to US dollars, but not for contagion between returns converted to euros? Arguing that only returns in US dollars are relevant to international investors, would be equally arbitrary as arguing that only returns in euros are important to them. Alternatively, one could claim that US dollar investors are interested in the outcomes based on US dollars, while euro investors are interested in the outcomes based on euro returns. This interpretation, however, is inconsistent with the idea that whether or not contagion occurred is not a matter of perspective. There either is or is not an investor panic spilling over between stock markets, say; it cannot be the case that such a panic occurs in the world of a US dollar investor, but not in the world of a euro investor. Contagion is not in the eye of the beholder.

The crucial element to note is that contagion is about transmission of changes in supply and demand across financial markets. These changes in supply and demand are most accurately reflected by market returns in local currencies, since only these returns fully come about in national stock markets themselves. Equation (3.1) shows that this property does not apply to returns converted to a common currency, since these are not only driven by supply and demand in national stock markets, but also by supply and demand in the market for foreign exchange. As a result, by converting the returns on two stock markets into for instance US dollars, a sudden depreciation of both local currencies against the dollar can create the impression of a synchronous fall

Table 3.1. Overview of contagion analyses using U.S. Dollar returns

Article	Method to analyse contagion	Motivation for dollar returns
Hamao, Masulis & Ng (1990)	Modelling market returns as GARCH-M processes while including returns from foreign stock markets	None
Lee & Kim (1993)	Correlation and factor analysis of stock market returns	None
King, Sentana & Wadhwani (1994)	Analysis of correlation between market returns implied by a factor model	None
Forbes & Rigobon (2002)	Analysis of heteroscedasticity-adjusted correlation between stock market returns	Follow common practice
Bae, Karolyi & Stulz (2003)	Analysis of the coincidence between extreme returns across stock markets	None
Rigobon (2003)	Analysis of changes in the determinant of market returns' covariance matrix	None
Chan-lau, Mathieson & Yao (2004)	Analysis of the probability that extreme returns coincide across stock markets	None
Baur & Schulze (2005)	Analysis of the (modified) coincidence between extreme returns across markets	None
Bekaert, Harvey & Ng (2005)	Analysis of correlation between residuals from a factor model fitted to market returns	None
Caporale, Cipolinni & Spagnolo (2005)	Modelling market returns as GARCH processes while including returns from foreign stock markets	None
Corsetti, Pericoli & Sbracia (2005)	Analysis of heteroscedasticity-adjusted correlation between stock market returns	None
Flavin & Panopoulou (2007)	Analysis of heteroscedasticity in the covariance matrix of market returns	Adopt international investor's perspective
Rodriguez (2007)	Analysis of changes in Kendall's tau implied by copula's fitted to stock market returns	None
Baur & Fry (2009)	Estimation of a panel regression model of market returns with time-fixed contagion effects	Adopt international investor's perspective
Baele & Inghelbrecht (2010)	Analysis of correlation between residuals from a factor model fitted to market returns	None
Dungey, Fry, Gonzalez-Hermosillo, Martin & Tang (2010)	Modelling market returns using latent factors and contagion channels	None

in the demand for stocks across markets, even when in reality there is none. The impact of changes in the dollar exchange rate is then effectively equal to the impact of a common shock driving the examined market returns. This insight has been overlooked by most previous research, even though it was already touched upon in a diversification study by Longin and Solnik (1995), who "use returns in local currency to focus on the correlation across markets rather than across currencies" (p. 21).

3.4 Empirical comparison

We examine the difference between US dollar returns and local currency returns empirically by focusing on the results from the regression

$$R^{\$}_{i,t} = \alpha_i + \beta R_{i,t} + \epsilon_{i,t}, \tag{3.2}$$

which regresses US dollar returns of country i on a constant and this country's local currency returns. We also run this regression for squared market returns, as contagion between the returns' volatility could be of interest as well (see for instance Baele 2005).

Table 3.2 reports the β coefficients from the regression equations, for all stock markets examined by Forbes and Rigobon (2002). We estimate these regressions for the three years since the start of the Global Financial Crisis in mid-2007, which comprise the period from Monday 2 July 2007 to Wednesday 30 June 2010. The first column reports the coefficient estimates obtained when regressing each country's US dollar returns on the corresponding local currency returns. The more this coefficient differs from one, the larger the difference between both types of market returns. The reported estimates vary between 0.87 and 1.40, with $t-$statistics for the test whether these coefficients are equal to one varying between -7.35 and 12.92. The third and fourth columns provide similar results for the regression using squared market returns, which are of interest when analysing contagion in stock market volatility. For these squared returns the coefficient estimates vary between 0.75 and 2.71, with $t-$statistics ranging from -13.62 to 40.93. Differences between US dollar and local currency returns can thus be substantial, and vary across countries in magnitude as well as in sign.

Figure 3.1 analyses whether differences between US dollar and local currency re-

Table 3.2. Similarity of local currency and US dollar returns

Regression equation: $R^{\$}_{i,t} = \alpha_i + \beta R_{i,t} + \epsilon_{i,t}$

		Returns		Squared returns	
Region	Country	β	t-stat.($\beta = 1$)	β	t-stat.($\beta = 1$)
East Asia	Hong Kong	1.00	0.80	1.00	-1.49
	Indonesia	1.15	6.25	1.31	12.56
	Japan	0.87	-7.35	0.75	-13.62
	Korea	1.37	6.81	2.71	31.19
	Malaysia	1.17	9.96	1.22	13.10
	Philippines	1.10	9.71	1.13	12.77
	Singapore	1.08	8.12	1.15	15.45
	Taiwan	1.07	9.34	1.17	21.31
	Thailand	1.04	6.06	1.06	9.67
Latin	Argentina	1.01	1.60	1.01	2.41
America	Brazil	1.26	9.82	1.75	28.83
	Chile	1.28	6.47	1.93	21.42
	Mexico	1.22	8.33	1.62	23.29
OECD	Australia	1.40	9.23	2.32	30.07
	Belgium	1.12	7.07	1.28	16.27
	Canada	1.17	6.79	1.41	16.73
	France	1.13	9.07	1.37	24.90
	Germany	1.13	8.61	1.30	19.01
	Italy	1.17	8.53	1.32	16.30
	Netherlands	1.12	7.94	1.34	21.86
	Spain	1.13	9.74	1.32	23.39
	Sweden	1.29	12.92	1.71	31.51
	Switzerland	0.98	-0.90	0.97	-1.39
	United Kingdom	1.17	8.26	1.51	24.70
Other	China	1.00	0.69	1.00	-2.03
emerging	India	1.13	12.42	1.29	28.37
markets	Russia	1.08	8.12	1.08	7.96
	South Africa	1.38	12.28	2.27	40.93

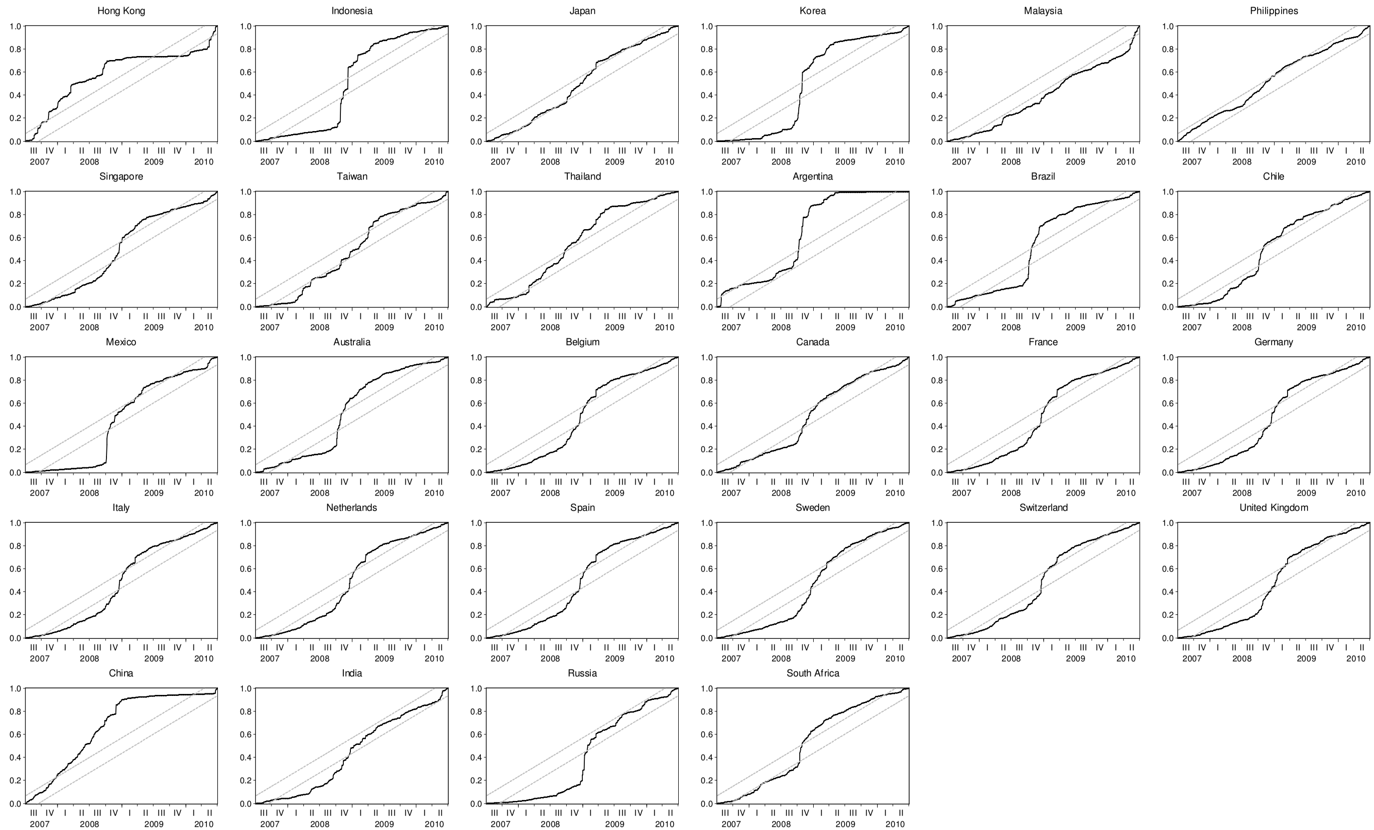
The examined sample period runs from 1 July 2007 to 30 June 2010. Returns are measured on a daily basis. The stock market indices used are the Hang Seng, Jakarta SE Composite, Nikkei 225 Stock Average, Korea SE Composite, KLCI Composite, Philippine SE I, MSCI Singapore, Taiwan SE Weighted, Bangkok SET, MSCI Argentina, Brazil Bovespa, Chil General (IGPA), Mexico IPC (Bolsa), ASX all ordinaries, BEL-20, S&P/TSX 60, CAC-40, DAX 30, FTSE Italia MIB Storico, AEX, IBEX 35, OMX Stockholm, Swiss Market Price Index, FTSE100, Shanghai SE Composite, India BSE 100, MSCI Russia, FTSE/JSE.

turns vary over time. The graphs report the sum of squared residuals from recursive estimation of the regression in Equation (3.2), i.e. repeated estimation of the regressions for ever larger subsets of the sample data, expressed as a percentage of the sum of squared residuals for the full-sample period. If the regression coefficient and model fit are constant over time, for gradually expanding sample sizes this ratio should increase from 0 to 1 within the indicated five percent confidence bounds. The graphs show that this ratio often is outside these bounds, while Figure 3.2 finds the same result for regressions using squared stock market returns. This result implies that the estimated β coefficients are not constant across the full sample period. Hence, while the finding from the table was that US dollar and local currency returns are different on average, the graphs show that the difference between both also changes over time.

For illustrative purposes, we investigate to what extent focusing on US dollar returns can bias results from the contagion test by Forbes and Rigobon (2002). These authors calculate an adjusted (for heteroscedasticity) correlation statistic between pairs of stock markets, and examine whether there is contagion between both markets by comparing the correlation between 'crisis' and 'tranquil' periods. As a large amount of alternative testing procedures have been proposed since Forbes and Rigobon's (2002) seminal work, this exercise is not meant as a formal test of contagion, but is only indicative of the bias that could arise when using US dollar returns to examine stock market contagion. We apply the Forbes and Rigobon (2002) contagion test to local currency as well as US dollar returns, and examine to what extent the $t-$statistics for the increase in correlations between the tranquil and crisis period differ across currencies. We calculate the adjusted correlation coefficient between the United States' market returns and the returns of each country in Table 3.2, examining the one-month crisis period following the collapse of Lehman Brothers on Monday 15 September 2008. We focus on the adjusted correlation between the residuals of a VAR(5) model in which all countries' return series are simultaneously included.

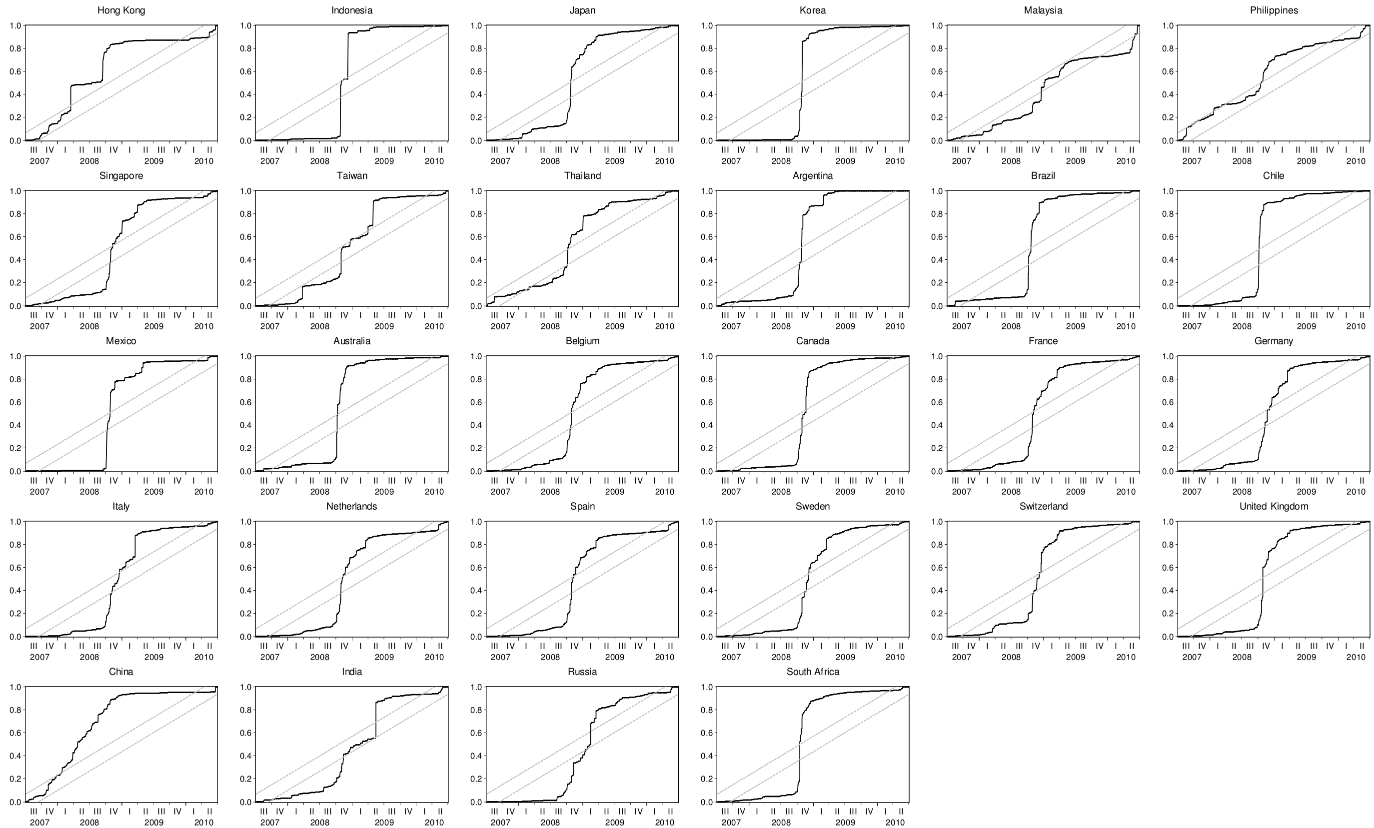
The results show that when defining the tranquil period as the full three-year period after 2 July 2007, $t-$statistics for US dollar returns are on average 0.25 points higher than those for local currency returns, while the correlation between both sets of $t-$statistics equals 0.85. When defining the tranquil period as year following Tuesday 1 July 2008, US dollar $t-$statistics are as much as 0.67 points higher than the ones for lo-

Figure 3.1. Development over time of similarity between US dollar and local currency returns



The graphs consider the recursive residuals from the regression of US dollar on local currency returns. The black lines at each date indicate the sum of squared recursive residuals up and until that date expressed as a percentage of the sum of squared recursive residuals for the full sample. If this ratio is outside the 95-percent confidence interval indicated by the gray lines, the relationship between both types of returns is not constant over time.

Figure 3.2. Development over time of similarity between squared US dollar and local currency returns



The graphs consider the recursive residuals from the regression of squared US dollar on squared local currency returns. The black lines at each date indicate the sum of squared recursive residuals up and until that date expressed as a percentage of the sum of squared recursive residuals for the full sample. If this ratio is outside the 95-percent confidence interval indicated by the gray lines, the relationship between both types of squared returns is not constant over time.

cal currency returns, whilst the correlation of US dollar with local currency $t-$statistics equals only 0.67. Using US dollar returns can thus bias the $t-$statistics on average, as well as bias countries' ranking based on these statistics. Depending on the chosen significance level, i.e. the chosen critical values for the $t-$statistics, this bias affects the conclusions on when and between which countries contagion has occurred. To avoid this bias from affecting the results of empirical contagion tests, we suggest to focus on stock market returns expressed in local currencies.

3.5 Conclusion

Having summarised the main definitions of contagion in the empirical literature, this chapter discusses the common practice to analyse stock market contagion by focusing on market returns converted to US dollars. This practice originated in the early literature on diversification between international stock markets, but we show that when analysing contagion such a conversion is inappropriate. The reason is that only returns denominated in local currencies accurately reflect supply and demand in national stock markets. For the 2007–2010 Global Financial Crisis, the differences between both types of returns turn out to be large due to the volatility of the dollar exchange rate, which is shown to bias the outcomes of a contagion test.

Chapter 4

Contagion from Stock Market Crises*

* This chapter is based on Mierau and Mink (2009).

4.1 Introduction

The behaviour of international stock markets illustrates why investors fear that during financial crises contagion occurs: while in tranquil times returns across markets correlate only mildly, the correlation between them tends to jump when sudden price drops occur. (see Chapter 3 for an overview of contagion definitions adopted in the literature).[1] This chapter examines contagion between stock markets in more detail by (i) introducing a measure of co-movement between stock markets that is new to the contagion literature, and (ii) by analysing how conclusions about contagion depend on the choice of the 'crisis' sample.

As our measure of co-movement we use the flexible measure of stock market synchronicity proposed by Morck, Yeung, and Yu (2000), and examine contagion by comparing synchronicity between various crisis and non-crisis samples. Morck, Yeung, and Yu (2000) use the measure to study synchronicity within a larger cross-section or region of stock markets, while we show that it can also be applied to synchronicity between a single market and the region as well as to synchronicity between a pair of stock markets. In a two-market setting, for instance, the measure indicates whether or not both markets move in the same direction, i.e. up or down. For our purpose, additional advantages of the measure are that it can be applied to periods as short as a single trading day, and that it does not require the market returns to be standardised (which could give results that are difficult to interpret when these returns are non-normal or heteroscedastic).

In order to differentiate between tranquil times and times of crisis, it is adamant to first define a 'crisis' sample. Doing so boils down to deciding upon the stock markets between which co-movement is to be analysed, and upon the trading days for which the analysis is to be performed. The stock markets to be analysed are generally chosen by first selecting a 'source' market from which any contagion effects could have originated, and then examine co-movement between this market and several other stock markets in the region. Selecting this source usually requires some subjective judgement by the researcher, for instance by assuming that contagion comes from the

[1] This chapter focuses on contagion between the mean of the returns, while alternatively Baele (2005) examines spillovers in their variance, and Fry, Martin, and Tang (2010) examine contagion between the skewness and kurtosis of the market returns.

country with the most developed stock market. When studying the 1997 Asian crisis, Hong-Kong is often seen to be the culprit while for the 2007 Global Financial Crisis the United States is regarded as the source. We examine synchronicity between individual markets and the region to analyse the robustness of these choices, and analyse synchronicity within the region as a whole to avoid selecting a source market altogether.

As is the case with the stock markets to be analysed, also choosing the trading days to be examined often requires some subjective judgement. Chapter 3 explained that, broadly speaking, two approaches exist: Forbes and Rigobon (2002) define a crisis period using a fixed time-frame after a critical event, while Bae, Karolyi, and Stulz (2003) define the crisis sample as a quantile of returns which are considered 'extreme' in the sense that they exceed a given threshold (this quantile may be an adjacent period but may also be a set of non-sequential trading days). Although both approaches can be seen as canonical for the literature, deciding upon their underlying criteria is not always straightforward. Over 90 years after the Great Crash it is still not clear what can be considered the critical event that sent markets crashing down. In a similar vein, it is not directly obvious what can be considered an extreme return. We take an eclectic stance on these issues and study the robustness of both dating methods by examining all possible combinations of starting dates and lengths for the crisis period, as well as all possible threshold values of extreme returns for the crisis quantile.

One of the major themes in the contagion literature is the question of how to control for common shocks driving the market returns, or, more broadly speaking, for their fundamental economic driving forces. King and Wadhwani (1990) assume that economic fundamentals are constant over time, and examine the difference between correlation in tranquil and crisis times. Forbes and Rigobon (2002) acknowledge that fundamentals can be time-varying, and suggest to 'adjust' the correlation in crisis times based on a model of fundamental stock market returns. Corsetti, Pericoli, and Sbracia (2005) refine this approach, and show that the specification of the fundamental returns model crucially determines how this correction should be implemented. Bekaert, Harvey, and Ng (2005) propose not to correct the co-movement measure itself, but instead estimate a model of fundamental stock market returns and then examine the correlation between its residuals. This way they avoid having to design an adjustment for the chosen co-movement measure. We follow their approach and use a Vector Autoregression (VAR) model with commonly used indicators of economic fundamentals to filter the market returns. In addition, we use local currency denominated returns to control for exchange rate fluctuations. If, in contrast, the local currency returns are converted into a common currency, a sudden depreciation of the common currency against the local currencies creates the impression of stock market co-movement where in reality there is none (see Chapter 3).

Our results show that contagion is a phenomenon more heterogeneous than already acknowledged in the literature. While it is common practice to report results for co-movement during a predefined 'crisis' sample, we find many combinations of countries and time periods or return quantiles for which synchronicity is significantly elevated. These sub-samples, however, cannot be related to particular 'crisis' countries, periods or thresholds.

Our findings complement the conclusions of Caporale, Cipollini, and Spagnolo (2005), who use a flexible approach to define crisis periods and find several outbreaks of contagion during the Asian crisis. However, while they analyse contagion within a window that tightly embraces the period commonly used for the Asian crisis, we show that even during periods not generally associated with crises market synchronicity increases. Furthermore, the synchronicity during periods normally associated with financial crises is not higher than the synchronicity during periods not normally associated with financial crises. In that sense, stock market fluctuations do not seem to be especially contagious during financial crises. Studying the determinants of excess co-movement might shed more light on the existence of contagion, and is a fruitful avenue for future research. In addition, there is nothing special about our method that limits its use to the analysis of international stock market contagion. Natural alternative applications would be to examine contagion in currency and bond markets (see, for instance Favero and Giavazzi 2002, Gravelle, Kichian, and Morley 2006) or to study the co-movement of individual stock prices (see, amongst others Barberis, Schleifer, and Wurgler 2005, Jin and Myers 2010).[2]

The remainder of this chapter is structured as follows. The next section introduces the synchronicity measure and discusses how to date financial crises. Section 4.3 applies the synchronicity measure to the 1997 Asian crisis and the 2007 Global Financial

[2] Mink, Jacobs, and de Haan (2012) use the measure to examine output gap coherence in the euro area.

Crisis. The final section provides an interpretation of our results and offers some concluding comments.

4.2 Method

4.2.1 Measuring stock market co-movement

Measuring stock market contagion amounts to studying the difference in co-movement in filtered market returns (see below) between tranquil times and times of crisis. In its purest form this boils down to performing a standard two-sample t-test:

$$t = \frac{f^{crisis} - f^{tranquil}}{S^{crisis} / \sqrt{T^{crisis}}} \sim t\,(\nu) \tag{4.1}$$

where f is the value of the co-movement measure, S indicates the measure's standard deviation and T equals the number of trading days. If the value of the (one-tailed) test statistic exceeds the critical value corresponding to the distribution's degrees of freedom $\nu = T^{crisis} - 1$ and the desired significance level, the t-test concludes that co-movement is higher during crisis periods than at tranquil times. Hence, a value of t above the critical value indicates the existence of contagion.[3]

In order to measure co-movement between stock market returns we use the synchronicity measure proposed by Morck, Yeung, and Yu (2000), which reads

$$f_{Nt} = \frac{\max[n_t^{up}, n_t^{down}]}{n_t^{up} + n_t^{down}} \tag{4.2}$$

where n_t^{up} is the number of markets in which returns increased at trading day t, n_t^{down} is the number of markets in which returns decreased, and N denotes the total number of markets being studied. Thus, f_{Nt} indicates the proportion of markets that were synchronised on trading day t. For $N = 2$ the measure equals 1 when both markets

[3] For simplicity we ignore the uncertainty surrounding the estimate for $f^{tranquil}$ when setting up the t-test. If we allow for this uncertainty, the denominator of the test is $\sqrt{S^2_{crisis}/T^{crisis} + S^2_{tranquil}/T^{tranquil}}$ and the degrees of freedom equal $\frac{\left(S^2_{crisis}/T^{crisis} + S^2_{tranquil}/T^{tranquil}\right)^2}{\left(S^2_{crisis}/T^{crisis}\right)^2/\left(T^{crisis}-1\right) + \left(S^2_{tranquil}/T^{tranquil}\right)^2/\left(T^{tranquil}-1\right)}$. In our empirical analysis, the values for $T^{tranquil}$ are large enough to avoid this simplification from biasing our test results.

move in the same direction, and 0 when both markets move in opposite directions. Synchronicity between a single country i and the rest of the N markets is denoted as f_{iNt}, which equals 1 when market i moves in the same direction as the majority of the other markets, and 0 otherwise. In keeping with Morck, Yeung, and Yu (2000), the averages of these measures over time are defined as f_N for synchronicity between N markets, and f_{iN} for synchronicity of market i with the rest of the N markets. We define $f_N^{tranquil}$ and $f_{iN}^{tranquil}$ as the values of synchronicity during tranquil periods, and f_N^{crisis} and f_{iN}^{crisis} as the values during the crisis period.

For sufficiently large N, Morck, Yeung, and Yu (2000) invoke the central limit theorem and relate the the difference between two observed synchronicity values to the normal distribution. We instead relate this difference to the $t-$distribution, but for $N = 2$ notice that synchronicity on a given trading day can only equal 0 or 1, and thus follows a binomial distribution. Therefore, for $N = 2$ we can test for a change in synchronicity by examining whether the number of synchronous trading days during the crisis period, $T^{crisis} f^{crisis}$, exceeds the critical value from the $\mathcal{B}\left(T^{crisis}, f^{tranquil}\right)$ distribution.[4] When analysing co-movement between a pair of markets using a measure of correlation, this measure would need to be Fisher-transformed before the $t-$test in Equation (4.1) can be applied.[5] The Fisher transformation, however, only applies when market returns are normally distributed, and has low discriminatory power when the examined crisis sample is small (see Dungey and Zhumabekova, 2001).

An advantage of measuring co-movement using the synchronicity measure instead of using a measure of correlation, is that synchronicity can be calculated directly from observed returns instead of from standardised returns.[6] Such standardised returns are obtained by demeaning and scaling the original market returns using the returns' population mean and standard deviation. As these population parameters are unobserved, they are usually estimated as the observed sample mean and standard error.

[4] Under the null-hypothesis that synchronicity during the crisis period f^{crisis} is equal to synchronicity during the tranquil period $f^{tranquil}$, the observed number of synchronous trading days during the crisis period $T^{crisis} f^{crisis}$ thus follows a binomial distribution with the number of observations being equal to the number of days in the crisis period T^{crisis}, and the probability of success being equal to synchronicity during the tranquil period $f^{tranquil}$.

[5] The Fisher-transformed correlation coefficient equals $\rho^* = 0.5 \ln (1+\rho) \;/\; (1-\rho)$, with ρ being the original sample correlation statistic.

[6] This is not the case for the correlation between market returns, as this metric is defined as the covariance between standardised stock market returns. Also the adjustments of the correlation coefficient that have been proposed in the contagion literature require the market returns to be standardised.

Table 4.1. Asian countries' stock market returns on 20 October 1997

	Original return	Standardised return - full period	Standardised return - crisis period
Hong Kong	-0.14	-6.22	-1.86
Indonesia	-0.09	-3.95	-2.63
Japan	-0.04	-2.85	-1.71
Korea	-0.07	-2.73	-1.44
Malaysia	-0.07	-2.54	-2.05
Philippines	-0.06	-3.35	-2.38
Singapore	-0.08	-4.76	-2.67
Taiwan	-0.06	-4.08	-1.89
Thailand	-0.06	-2.70	-1.98

The stock market indices are obtained from Thomson Datastream, and include the Hang Seng, Jakarta SE Composite, Nikkei 225 Stock Average, Korea SE Composite, KLCI Composite, Philippine SE I, MSCI Singapore, Taiwan SE Weighted, and the Bangkok SET, all expressed in local currencies. The full-sample period runs from 1 January 1996 to 31 December 1998, the crisis period is taken from Forbes and Rigobon (2002) and runs from Friday 17 October 1997 to Friday 14 November 1997.

However, in times of stock market turmoil such estimates may be biased since market returns can be non-normal or heteroscedastic during such periods.

Consider, for instance, Table 4.1, which shows that the actual stock market return in Hong Kong on 20 October 1997 equals -14 percent. Standardising this return using the population mean and standard deviation estimated over the full 1996–1998 sample suggests that the stock market return on 20 October 1997 is more than six standard deviations below the population average. In contrast, standardising the return using the population mean and standard deviation estimated over the Forbes and Rigobon (2002) crisis period, i.e. the period from Friday 17 October 1997 to Friday 14 November 1997, suggests it is less than two standard deviations below this average. The correlation between the actual returns and the crisis-sample standardised returns in column three only equals 0.12. Standardised returns are therefore difficult to interpret when the underlying returns are non-normal or heteroscedastic, and, hence, so is the co-movement between them.

4.2.2 Determining the crisis sample

Besides having to define a measure of stock market co-movement, it follows from Equation (4.1) that to test for contagion we need to decide which periods are to be identified as crisis periods and which are to be defined as tranquil. Forbes and Rigobon (2002) use an 'event' approach and define the crisis period for the Asian crisis to run from Friday 17 October 1997 to Friday 14 November 1997. On the first trading day of this period the Hong Kong Stock exchange dropped by as much as 14 percent, while it lost about 27 percent of its value during this entire month. We interpret this dating method as implying that a crisis starts with a critical event and then eases out over a one-month period. We apply this method to the Global Financial Crisis by letting the crisis period run from Monday 15 September 2008 to Monday 13 October 2008, thus starting on the day that the US investment bank Lehman Brothers went into administration. As our second dating method we use the approach by Bae, Karolyi, and Stulz (2003), who propose to define the crisis as the quantile of trading days in which returns were below the 5^{th} percentile of the returns distribution. Note that this approach allows for crisis periods that need not be sequential. That is, it may be that two trading days are identified as part of the crisis sample even though there was a tranquil day in between.[7]

Dating crises on the basis of the approaches by Forbes and Rigobon (2002) and Bae, Karolyi, and Stulz (2003) covers the two most common approaches used in the literature, i.e. defining the crisis sample as an adjacent time period or as a set of trading days on which returns can by some measure be considered 'extreme'. A disadvantage of both methods, however, is that they require defining the crisis sample based on a fixed criterion, that is, they in advance define the starting date and the length of the crisis period, or the percentile for the crisis quantile. To test the robustness of these choices, we analyse all potential crisis samples that can be generated in line with the above two dating approaches.

We vary the starting date and length of the period in all possible ways. This exercise

[7] Applying the synchronicity measure to extreme returns is related to the coexeedance approach of Bae, Karolyi, and Stulz (2003). We examine contagion by testing whether synchronicity between extreme returns is higher than synchronicity between all returns, while Bae, Karolyi, and Stulz (2003) examine contagion by testing whether synchronicity between extreme returns is higher than synchronicity between extreme returns generated from statistical models of countries' stock market returns.

requires that for each trading day in the sample, we examine crisis periods that start on this date and have a length of $1, 2, ..., \tau$, with τ being the number of days until the end of the sample. This approach can be interpreted as a rolling window exercise as proposed by Billio and Pelizzon (2003), where we examine windows of all possible lengths. As the synchronicity measure can be calculated on a daily basis we can even study crisis periods as short as a single trading day.

To analyse all potential crisis quantiles, we vary the cut-off point from where a return is deemed extreme. To this end, we define the kth crisis quantile as the set of trading days during which at least one of the countries in the region experienced one of its k percent most negative stock market returns, where $k = 1, 2, ..., 100$. As a result, we gain insight into whether the synchronicity between markets depends on the returns' amplitude. For all these different crisis samples, we examine whether synchronicity differs significantly from its full-sample average using the approach described in Section 4.2.

4.3 Results

We use the synchronicity measures to analyse contagion between Asian countries' stock markets during the financial crisis of 1996–1998, and between Western countries' stock markets during the Global Financial Crisis of 2006–2008. We examine the synchronicity of individual stock markets with Hong Kong, with the United States, with the region, and within the region as a whole. In order to control for the impact of economic fundamentals on market returns, Forbes and Rigobon (2002) and Dungey, Fry, Gonzales-Hermosillo, and Martin (2005) filter the returns of the stock markets with a daily Vector Autoregression while including the short term US interest rate as a common factor driving market returns. Similarly, Bekaert, Harvey, and Ng (2005) and Baur and Fry (2009) filter the returns with a Morgan Stanley Capital International (MSCI) world index as the common factor. The advantage of using the MSCI world index is that it captures more common economic forces present in the market than purely the US interest rate. Hence, we follow this approach and filter the market returns using a VAR with 5 lags (i.e. the length of the trading week) and the MSCI world index included as an exogenous variable.[8]

A sometimes overlooked but equally important common factor is the currency in which the returns on the stock markets under scrutiny are measured (see Chapter 3). For example, if two non-synchronous stock market returns are converted into a common currency and both currencies simultaneously depreciate or appreciate against this common currency, the stock market returns would seem to be synchronous also when they are not. Hence, we follow Longin and Solnik (1995), and "use returns in local currencies to focus on the correlation across markets rather than across currencies."

We assume that the above filtering procedure corrects for the impact of any common factors on the market returns, so that we can attribute any changes in the synchronicity between the filtered returns to contagion effects. This is in line with Bekaert, Harvey, and Ng (2005), although these authors use a more sophisticated model of asset returns. Our findings are thus conditional upon the specification of the filtering procedure, a point most clearly made by Corsetti, Pericoli, and Sbracia (2005). These authors also explain that this caveat necessarily applies to all analyses of contagion, basically because co-movement in excess of fundamentals cannot be established before taking a stance on what these unobserved fundamentals actually are (see also Chapter 4). While the analysis below does not escape from this vulnerability either, we believe its conclusions are sufficiently general to hold also in the presence of this caveat.

4.3.1 The 1997 Asian crisis

In the run-up to the Asian crisis, countries in the region had experienced large foreign capital inflows, which spurred economic growth and thereby gave rise to the idea of an 'Asian miracle'. From the mid-1990s this perception changed, leading to speculative attacks against the Thai Baht during May 1997. These attacks forced the Thai government to abandon the peg to the US dollar, marking what is now considered to be the start of the Asian crisis. During this period countries in the region were confronted with large capital outflows. Figure 4.1 shows that these outflows had a large impact on stock markets as well. For some of these countries the stock market decline lasted the full period, while for notably Hong Kong and Taiwan they started only after mid-

[8] Using alternative specifications for the VAR model does not qualitatively affect our conclusions.

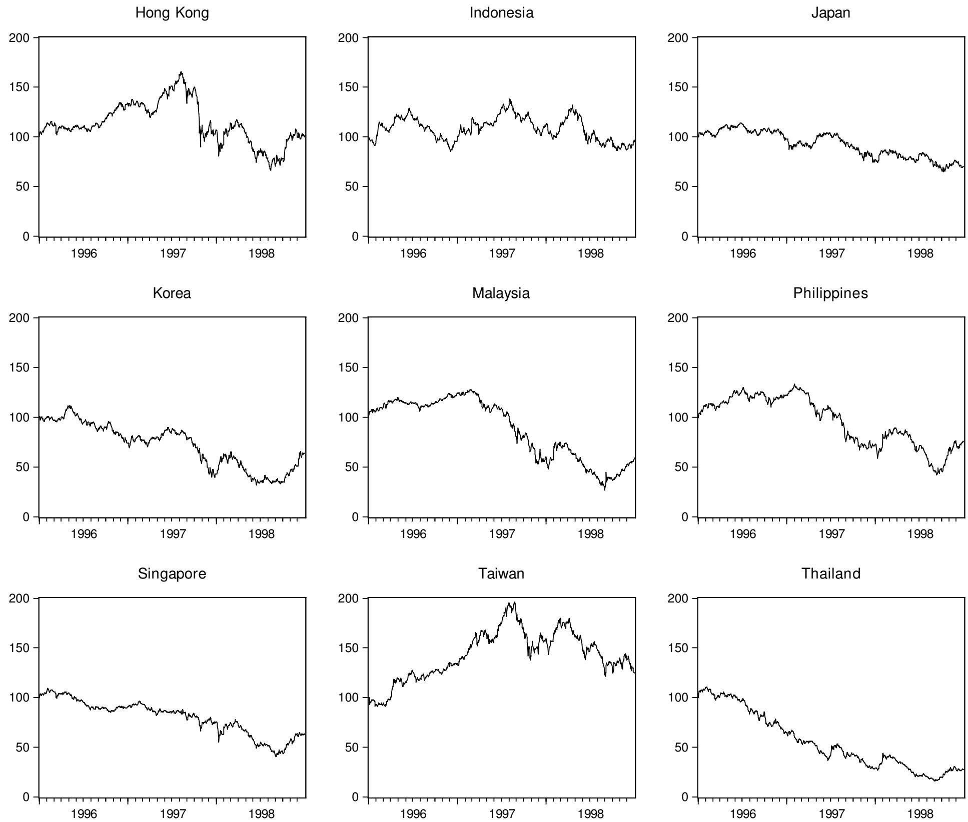
1997. The 27 percent fall of the Hong Kong index following Friday 17 October 1997 is clearly the largest stock market crash observed in the sample.

Table 4.2 reports the results of a contagion analysis for our two alternative approaches to identify the crisis sample. The first approach is based on Forbes and Rigobon (2002), who take the one-month period starting on Friday 17 October 1997, the date after which the Hong Kong index collapsed. The second approach is based on Bae, Karolyi, and Stulz (2003), who focus on the quantile of trading days with the 5 percent most negative returns observed during the full-sample period. We examine whether synchronicity during both sub-samples differs significantly from synchronicity during the full-sample period, which runs from 1 January 1996 to 31 December 1998. The reported p-values indicate the probability that synchronicity is constant across both samples.

The first rows in the table report the synchronicity of individual stock markets with Hong Kong, which Forbes and Rigobon (2002) assume to be the source of any contagion effects. As can be seen, synchronicity between for instance Indonesia and Hong Kong over the full-sample is 0.61, whereas it equals 0.76 during the examined crisis period. The third column shows that this increase in synchronicity is not statistically different from zero at the five percent level of significance, which holds for the other countries as well. For Taiwan, synchronicity during the crisis period is actually significantly lower than during the full sample. During the crisis quantile based on Bae, Karolyi, and Stulz (2003), synchronicity between Indonesia and Hong Kong amounts to 0.61, which is exactly the same as synchronicity for the full-sample period. With the exception of Singapore, synchronicity during the crisis quantile is never significantly higher than its full-sample average.

The analysis so far assumes that Hong Kong was the source of any contagion effects. As synchronicity of Hong Kong with the other countries in the sample is almost never significantly elevated, we relax this assumption and in the next rows examine synchronicity of each individual country with the region f_{iN}. When this level is significantly higher than during the full-sample period, it becomes more likely that the country examined was the source of any contagion effects to the rest of the region. For the crisis period by Forbes and Rigobon (2002) we never find synchronicity to be significantly elevated, but for the crisis quantile by Bae, Karolyi, and Stulz (2003) it is

Figure 4.1. Asian countries' stock market indices during 1996–1998 (January 1st 1996 = 100)



The reported stock market indices are obtained from Thomson Datastream, and include the Hang Seng, Jakarta SE Composite, Nikkei 225 Stock Average, Korea SE Composite, KLCI Composite, Philippine SE I, MSCI Singapore, Taiwan SE Weighted, and the Bangkok SET, all expressed in local currencies.

Table 4.2. Synchronicity between Asian countries for crisis sub-samples during 1996–1998

		Dating Forbes and Rigobon (2002)		Dating Bae, Karolyi and Stulz (2003)	
	Full-sample	Crisis period	p-value	Crisis quantile	p-value
Synchronicity with Hong Kong (f_{ij})					
Indonesia	0.61	0.76	0.10	0.61	0.51
Japan	0.54	0.57	0.48	0.57	0.26
Korea	0.51	0.52	0.53	0.47	0.87
Malaysia	0.60	0.67	0.34	0.65	0.10
Philippines	0.59	0.71	0.31	0.60	0.38
Singapore	0.64	0.71	0.50	0.70	0.04
Taiwan	0.56	0.33	0.99	0.60	0.14
Thailand	0.58	0.62	0.46	0.59	0.48
Synchronicity with the region (f_{iN})					
Hong Kong	0.74	0.76	0.51	0.74	0.51
Indonesia	0.73	0.81	0.31	0.74	0.46
Japan	0.63	0.62	0.64	0.65	0.29
Korea	0.62	0.67	0.42	0.58	0.91
Malaysia	0.72	0.81	0.26	0.78	0.05
Philippines	0.70	0.76	0.37	0.72	0.33
Singapore	0.78	0.67	0.93	0.80	0.26
Taiwan	0.64	0.57	0.81	0.71	0.02
Thailand	0.71	0.76	0.39	0.70	0.59
Synchronicity within the region (f_N)	0.70	0.71	0.31	0.71	0.05

The stock market indices are obtained from Thomson Datastream, and include the Hang Seng, Jakarta SE Composite, Nikkei 225 Stock Average, Korea SE Composite, KLCI Composite, Philippine SE I, MSCI Singapore, Taiwan SE Weighted, and the Bangkok SET, all expressed in local currencies. The full-sample period runs from 1 January 1996 to 31 December 1998, the crisis period by Forbes and Rigobon (2002) runs from 17 October 1997 to 14 November 1997, and the crisis period by Bae, Karolyi and Stulz (2003) equals all days during which at least one of the countries experienced a return in the 5 percent quantile. P-values indicate the probability that synchronicity is constant across the full-sample and the crisis period.

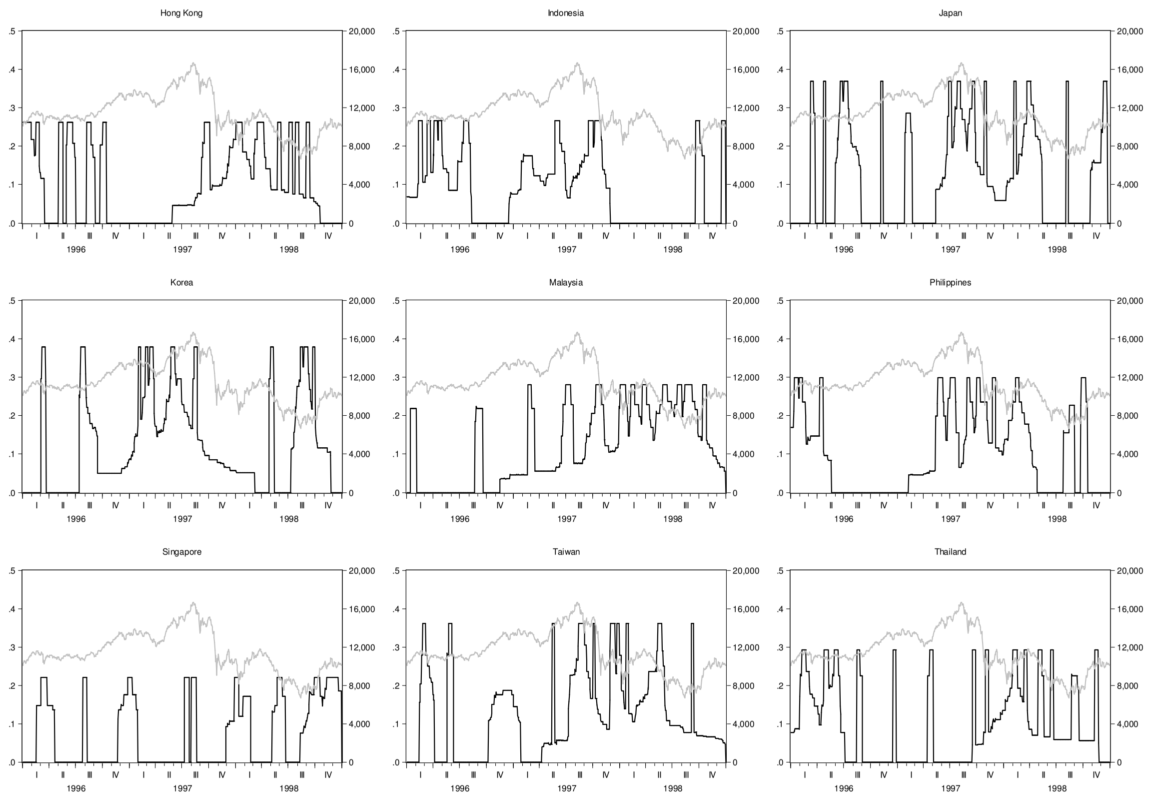
significantly higher for Malaysia and Taiwan. Synchronicity between Hong Kong and the region during both crisis samples is not significantly different from its full-sample value. The last row shows that also synchronicity within the region f_N is significantly higher during the crisis quantile, but not during the crisis period.

The limited evidence for contagion from the above analysis not only casts doubt on the assumption that Hong Kong was the 'source' of any contagion effects, but also raises the question of whether the chosen 'crisis' samples are the correct ones. Hence, we relax both these assumptions and examine synchronicity between individual countries and the region f_{iN} and within the region f_N as a whole for all crisis samples possible over the full 1996–1998 time period. For the crisis dating approach by Forbes and Rigobon (2002), this exercise implies that we examine crisis periods with all possible starting dates and with lengths varying between $1, 2, ..., \tau$, with τ being the number of days from the starting date to the end of the sample. For the crisis dating approach by Bae, Karolyi, and Stulz (2003), we examine crisis quantiles by focusing on trading days during which at least one of the countries in the region experienced a return below a given threshold value, where we vary this threshold in such a manner that the quantile includes the k percent most negative stock market returns, with $k = 1, 2, ..., 100$. For all these different crisis periods and quantiles, we examine whether synchronicity differs significantly from its full-sample average.

Figure 4.2 reports the results for the dating approach based on Forbes and Rigobon (2002). The figure shows all periods for which synchronicity between individual countries and the region f_{iN} was higher than the full-sample average at the five percent level of significance. The left axis indicates by how much synchronicity was elevated, while the bottom axis indicates over which time period this was the case. The right axis indicates the level of the Hong Kong stock market index. The upper left graph for instance shows that synchronicity between Hong Kong and the region was significantly increased by about 0.05 points from 1997Q3 to 1998Q4. Within this period, synchronicity was significantly elevated by a larger amount during several sub-periods, such as the last month of 1997Q3 where it was 0.26 points higher than the full-sample value. Between 1996Q4 and 1997Q3, and during all possible sub-periods within this interval, synchronicity was never significantly different from the full-sample level.

As the graphs in the figure show, synchronicity between individual countries and

Figure 4.2. Synchronicity of Asian countries with the region for all potential crisis periods during 1996–1998



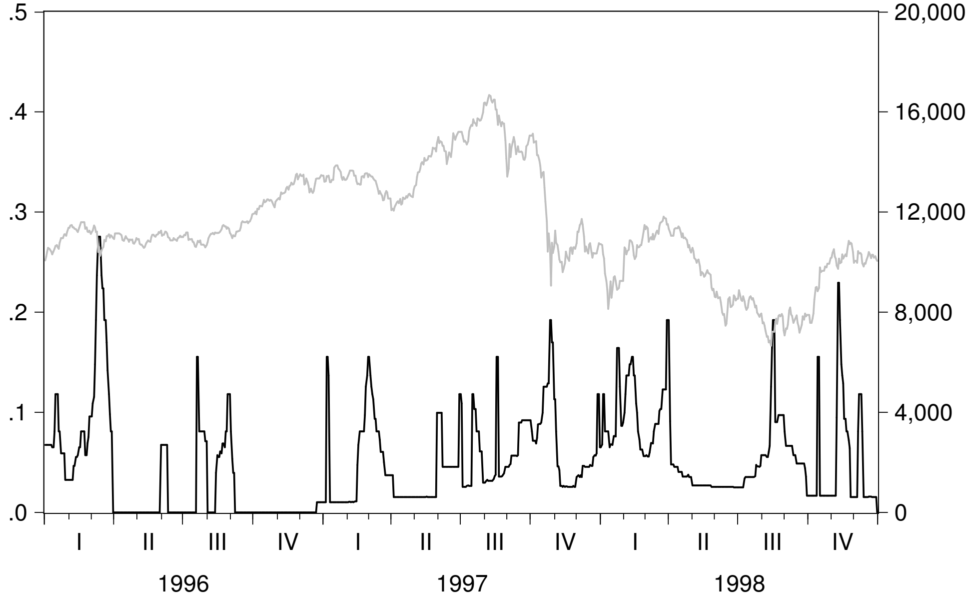
The figure shows all periods for which synchronicity f_{iN} was higher than the full-sample average at the five percent level of significance. The left axis indicates by how much synchronicity was elevated, while the bottom axis indicates over which time period this was the case. The right axis indicates the level of the Hong Kong stock market index (gray line).

the region is significantly higher than its full-sample average for several sub-sample periods. These periods vary in length and starting date, and differ across countries. While they sometimes coincide with the crash of the Hong Kong index in October 1997, many of these periods are unrelated to this event. In fact, around the time of the crash, synchronicity between Hong Kong and the region is less elevated than during many other sub-sample periods. These results suggest that there is not a clear 'source' country of any contagion effects, since each country now and then experiences significantly elevated synchronicity with the region. In addition, the results suggest that there is no clear 'crisis' period, since many periods can be found during which synchronicity is elevated.

Analogous to Figure 4.2, Figure 4.3 reports for which periods synchronicity within the region as a whole f_N was higher than its full-sample average. For instance, for the 1997–1998 period synchronicity was significantly elevated by about 0.01 points, while during several sub-periods within this interval it had increased by more than 0.15 points. The figure confirms that periods of increased synchronicity vary in length and starting date, and do not seem to be especially associated with the Hong Kong stock market crash. While synchronicity is significantly higher by 0.13 points on 20 October 1997, the first day on which the index started to fall, it is much more elevated during several other periods. Sometimes synchronicity is significantly different from its full-sample average during periods as short as two trading days. A correlation analysis would not be able to bring this observation to the fore, since the sample correlation between stock markets cannot be calculated for such short time periods.

Figures 4.4 and 4.5 report the results for the dating approach based on Bae, Karolyi, and Stulz (2003), again focusing on synchronicity between individual countries and the region f_{iN}, and on synchronicity within the region as a whole f_N. The bottom axis indicates the crisis quantile under consideration, with the value of 5 for instance indicating the quantile comprising the five percent most negative returns (as used for the analysis in Table 4.2). The left axis indicates the probability that synchronicity for this crisis quantile was equal to its full-sample average, with values closer to zero signalling that synchronicity was elevated during the crisis quantile (the scale is inverted so that an increase in the graph is associated with higher synchronicity). As before, we interpret p-values lower than 5 percent as a rejection of the null-hypothesis that

Figure 4.3. Synchronicity within the Asian region for all potential crisis periods during 1996–1998



The figure shows all periods for which synchronicity f_N was higher than the full-sample average at the five percent level of significance. The left axis indicates by how much synchronicity was elevated, while the bottom axis indicates over which time period this was the case. The right axis indicates the level of the Hong Kong stock market index (gray line).

synchronicity is equal to its level during the full-sample period.

The patterns in Figure 4.4 show that synchronicity between individual countries and the region is generally not higher when one of these countries experiences an extremely negative stock market return. The only exceptions to this observation are Malaysia, which experiences significantly higher synchronicity levels when the crisis sample comprises returns in the lower 1, 2, 5, 6, and 10 percent of the distribution, and Taiwan for crisis samples comprising returns amongst the 3 to 9 percent most negative ones of the distribution. For Japan, in contrast, synchronicity with the region is significantly lower when one of the countries experiences a highly negative market return. For all other countries, synchronicity in the crisis sample is generally not significantly higher than synchronicity during the full-sample period. Again, our results provide no evidence for the existence of a particular 'source' country or 'crisis' quantile associated with any contagion effects.[9]

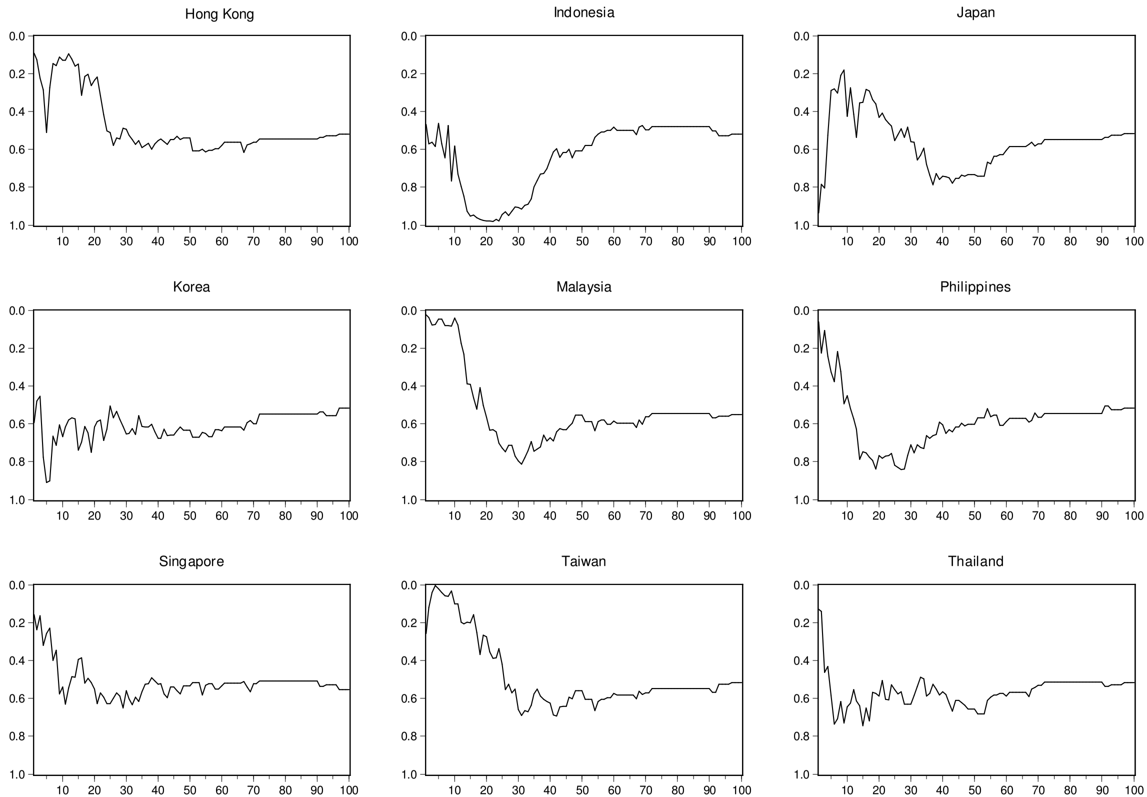
Figure 4.5 reports the results for synchronicity in the region as a whole. While synchronicity was already found to be elevated when we focus on the 5 percent most negative returns, see Table 4.2, it is also significantly elevated when we change this threshold to 1, 2, 3, 4, 7, 8, or 9 percent. In general, the p-values tend to increase gradually when the crisis quantile is expanded and less extreme returns are included as well. The figure thus shows that synchronicity within the region is higher when an extreme return is observed, but at the same time makes clear there is no natural extreme return threshold to distinguish a 'crisis' and a 'tranquil' sub-sample.

4.3.2 The 2007 Global Financial Crisis

The Global Financial Crisis started during the middle of 2007 with the burst of the US housing bubble accompanied by rising default rates on mortgages sold in the subprime market segment. While this first affected mortgage originators themselves, the crisis quickly spread through financial markets because these parties had transferred default risk on originated mortgages to third party investors on a large scale by selling mortgage-backed securities. Since such securities were also widely used as collateral

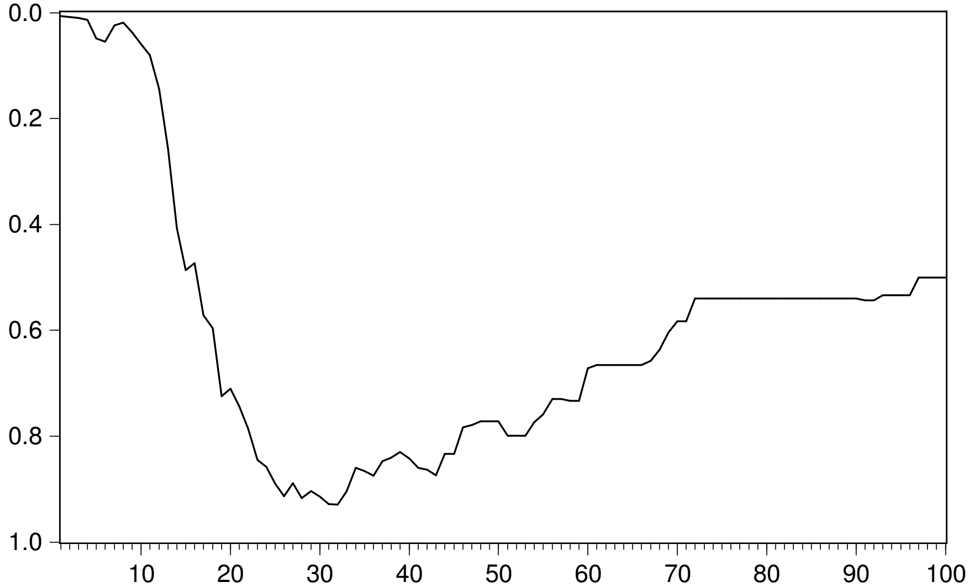
[9] The p-values in the graphs converge to 0.5 when the crisis sample becomes larger, reflecting the fact that synchronicity during the crisis sample then converges to synchronicity during the full-sample period. The probability that one of both values is larger than the other then exactly equals fifty percent.

Figure 4.4. Probability of constant synchronicity of Asian countries with the region for all potential crisis quantiles during 1996–1998



The bottom axis indicates the percentage of extreme negative returns included in the crisis quantile, while the (inverted) left axis indicates the probability that synchronicity f_{iN} for this crisis quantile was equal to its full-sample average.

Figure 4.5. Probability of constant synchronicity within the Asian region for all potential crisis quantiles during 1996–1998



The bottom axis indicates the percentage of extreme negative returns included in the crisis quantile, while the (inverted) left axis indicates the probability that synchronicity f_N for this crisis quantile was equal to its full-sample average.

in markets for wholesale funding, the increasing mortgage default rates and the rise in risk premiums caused by this development triggered the 2007 Global Financial Crisis.[10] Also stock markets were affected, especially in countries with relatively large financial sectors such as Belgium, France, Germany, Iceland, Ireland, the Netherlands, Switzerland, the United Kingdom and the United States. Figure 4.6 shows that since mid-2007 these countries' stock market indices declined almost in parallel.

Table 4.3 reports results similar to those reported in Table 4.2 for the 1997 Asian crisis. We define the crisis period based on the approach by Forbes and Rigobon (2002) as the month following the major crisis event in the sample, which we choose to be the collapse of Lehman Brothers on Monday 15 September 2008. For the crisis quantile based on Bae, Karolyi, and Stulz (2003) we again focus on those days where one of the countries experienced a negative return in the 5 percent tail of the distribution.

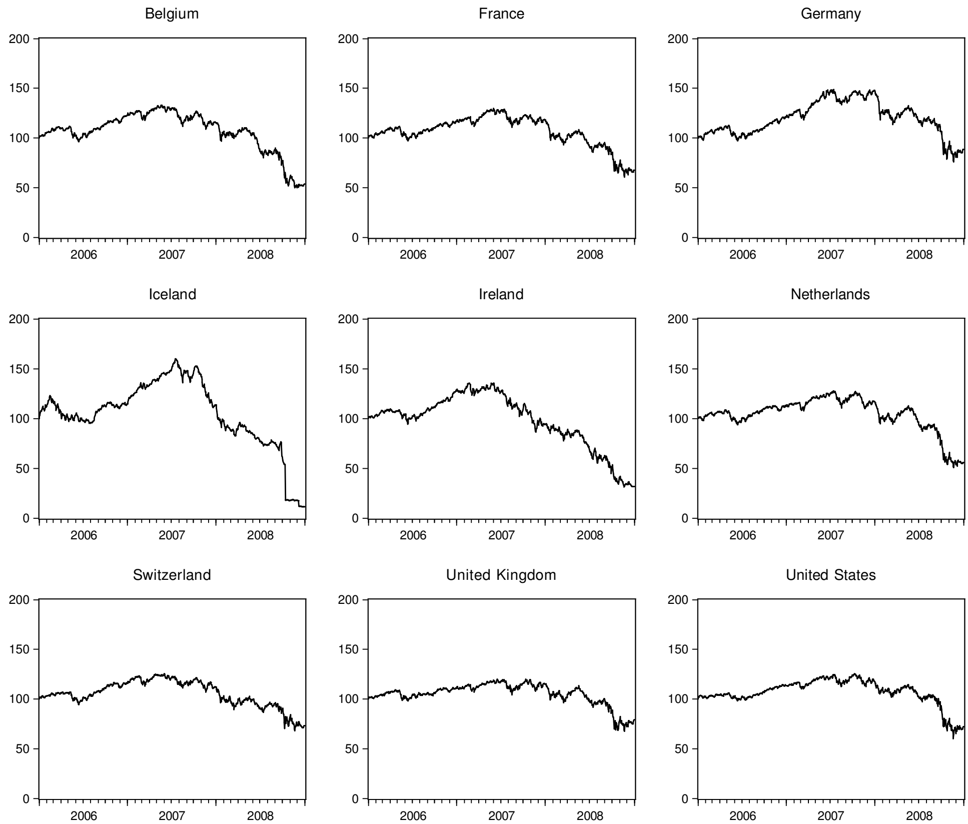
The first rows in the table report synchronicity between individual countries and the United States, which could be considered the source of any contagion effects. For the crisis period based on Forbes and Rigobon (2002) this measure turns out to be significantly elevated for France, Germany, and the United Kingdom, with the increase in synchronicity amounting to about 0.20 points. For the crisis sub-sample based on Bae, Karolyi, and Stulz (2003) we find a significant increase in synchronicity for Germany only.

We now relax the assumption of the United States being the source of any contagion effects, and focus in the next rows of the table on the results for synchronicity of each individual country with the region f_{iN}. It turns out that synchronicity between an individual country and the region is never significantly elevated, neither for the crisis period by Forbes and Rigobon (2002) nor for the crisis quantile by Bae, Karolyi, and Stulz (2003). Also synchronicity between the United States and the region is only significantly higher at the ten-percent level during the crisis period. Synchronicity within the region as a whole is significantly higher for the crisis period as well as the crisis quantile.

Figure 4.7 examines whether any other combinations of countries and time periods can be found during which synchronicity with the region f_{iN} significantly increased relative to the full-sample value. The figure shows that for France, Ireland, Switzer-

[10] Brunnermeier (2009) provides an extensive discussion of the chain of events.

Figure 4.6. Western countries' stock market indices during 2006–2008 (January 2[nd] 2006 = 100)



The reported stock market indices are obtained from Thomson Datastream, and include the BEL 20, CAC 40, DAX 30, OMX Iceland All-share, ISEQ Overall Index, AEX Index, SMI, FTSE 100, and S&P 500 (at 16:00 GMT), all expressed in local currencies.

Table 4.3. Synchronicity between western countries for crisis sub-samples during in the Global Financial Crisis for predefined crisis samples

		Dating Forbes and Rigobon (2002)		Dating Bae, Karolyi and Stulz (2003)	
	Full-sample	Crisis period	p-value	Crisis quantile	p-value
Synchronicity with the United States (f_{ij})					
Belgium	0.63	0.67	0.44	0.69	0.12
France	0.70	0.90	0.03	0.73	0.27
Germany	0.65	0.86	0.03	0.74	0.03
Iceland	0.50	0.52	0.49	0.52	0.33
Ireland	0.63	0.67	0.47	0.66	0.33
Netherlands	0.68	0.86	0.06	0.75	0.07
Switzerland	0.67	0.71	0.43	0.66	0.66
United Kingdom	0.70	0.90	0.03	0.76	0.11
Synchronicity with the region (f_{iN})					
Belgium	0.79	0.67	0.94	0.82	0.25
France	0.89	1.00	0.08	0.92	0.14
Germany	0.82	0.86	0.49	0.82	0.62
Iceland	0.58	0.43	0.94	0.58	0.51
Ireland	0.69	0.67	0.71	0.75	0.12
Netherlands	0.84	0.95	0.13	0.89	0.13
Switzerland	0.77	0.81	0.47	0.81	0.23
United Kingdom	0.84	0.90	0.30	0.88	0.16
United States	0.75	0.90	0.08	0.79	0.23
Synchronicity within the region (f_N)	0.77	0.80	0.00	0.81	0.00

The stock market indices used are the BEL 20, CAC 40, DAX 30, OMX Iceland All-share, ISEQ Overall Index, AEX Index, SMI, FTSE 100, and S&P 500 (at 16:00 GMT), all expressed in local currencies. The full-sample period runs from 1 January 2006 to 31 December 2008, the crisis period by Forbes and Rigobon (2002) runs from 15 September 2008 to 13 October 2008, and the crisis period by Bae, Karolyi and Stulz (2003) equals all days during which at least one of the countries experienced a return in the 5 percent quantile. P-values indicates the probability that synchronicity is constant across the full-sample and the crisis period.

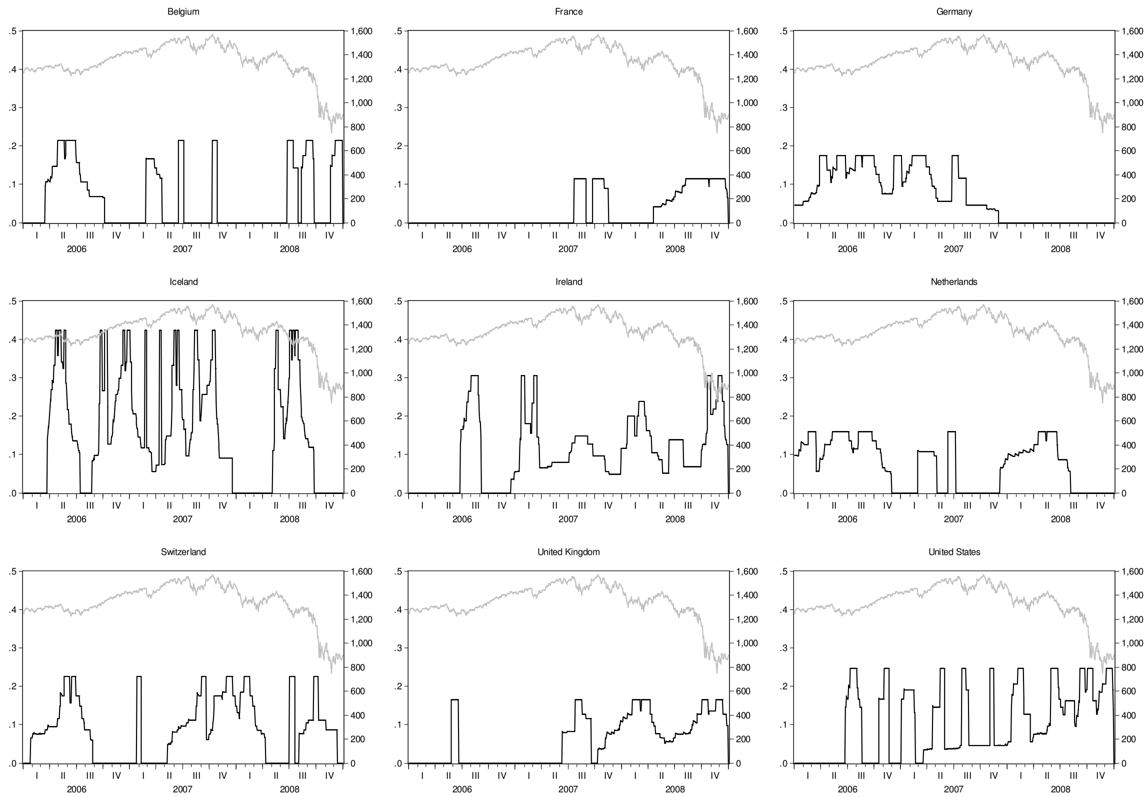
land, the United Kingdom, and the United States, synchronicity with the region is indeed significantly higher during the aftermath of the Lehman collapse. This is not the case for the other countries in the sample, while for all countries synchronicity is elevated during several sub-sample periods that cannot be associated with the collapse. This amount of sub-sample periods seems to be somewhat smaller than the amount for the Asian crisis reported in Figure 4.2, which suggests that during the Global Financial Crisis the interaction between stock markets was more stable. As was the case for the East-Asian crisis, the graphs do not provide clear evidence for a 'source' country or 'crisis' country during for which any contagion effects were particularly pronounced.

Figure 4.8 examines synchronicity within the region for alternative crisis periods. While the graph confirms that synchronicity significantly increased around the collapse of Lehman Brothers, during many periods around this event it is elevated by much more than the 0.03 points reported in Table 4.3 for the crisis month identified based on Forbes and Rigobon (2002). In addition, the graphs show that the increases in synchronicity around September 2008 are smaller than several increases observed during sub-sample periods unrelated to the Lehman turmoil. The analysis thus confirms our finding from the Asian crisis that periods of elevated synchronicity vary in length and starting date, and do not seem to be associated with particular crisis events.

Figure 4.9 reports p-values for the test whether synchronicity is constant for alternative crisis samples defined on the basis of Bae, Karolyi, and Stulz (2003). Again, in most cases the graphs do not provide much evidence for synchronicity being significantly higher during trading days with extreme returns. For France, the increase in synchronicity is only significant for the 11 percent most negative returns, for Ireland for the 2 to 4 percent most negative returns, and for the United States for the 2 percent most negative returns. For several other countries, synchronicity on days with extreme returns lies below the full-sample average, and even significantly so for Belgium and Iceland for the 1 percent most negative returns. These findings again provide little evidence for the existence of a 'source' country or 'crisis' quantile.

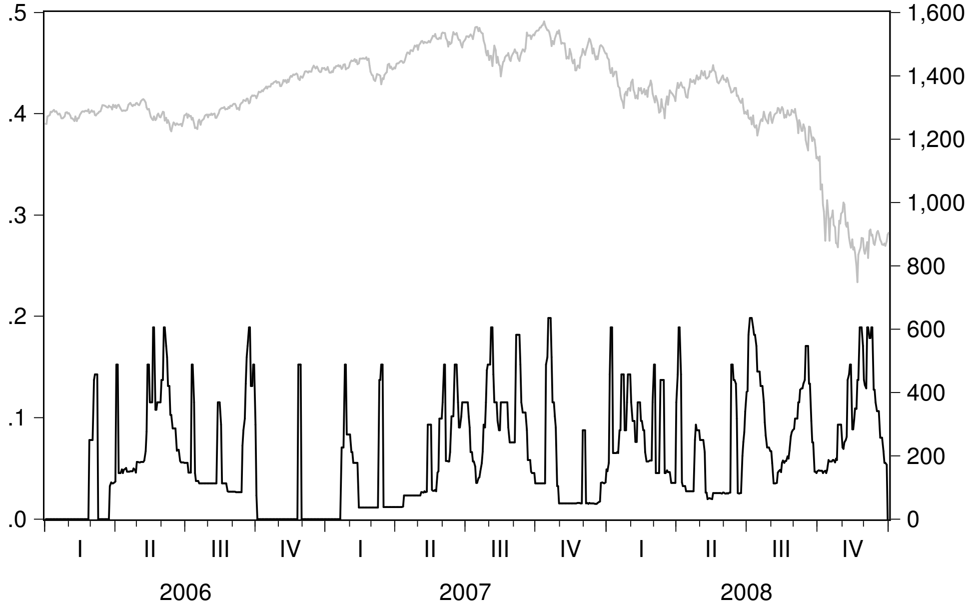
Figure 4.10 shows that synchronicity within the region as a whole, f_N, is significantly elevated for the 2 to 11 percent most negative returns. The graph shows that there is no natural extreme return threshold to separate a 'crisis' and a 'tranquil' subsample.

Figure 4.7. Synchronicity of Western countries with the region for all potential crisis periods during 2006–2008



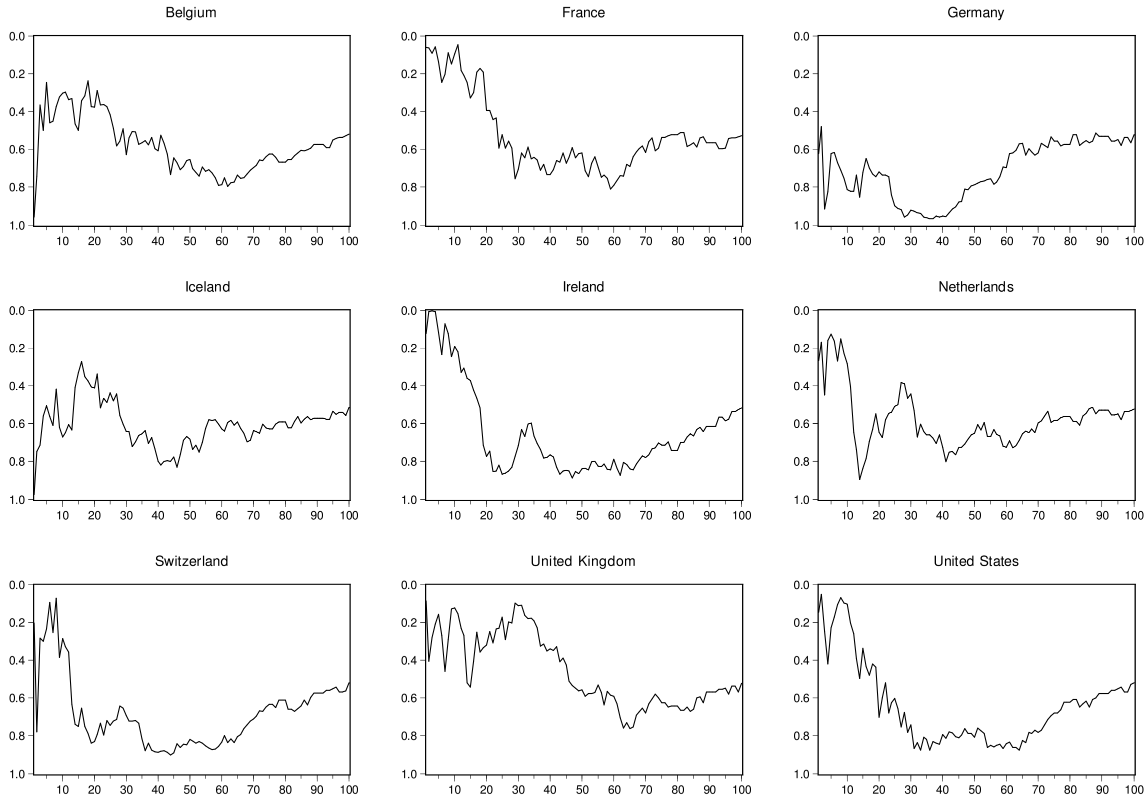
The figure shows all periods for which synchronicity f_{iN} was higher than the full-sample average at the five percent level of significance. The left axis indicates by how much synchronicity was elevated, while the bottom axis indicates over which time period this was the case. The right axis indicates the level of the US stock market index (gray line).

Figure 4.8. Synchronicity within the Western region for all potential crisis periods during 2006–2008



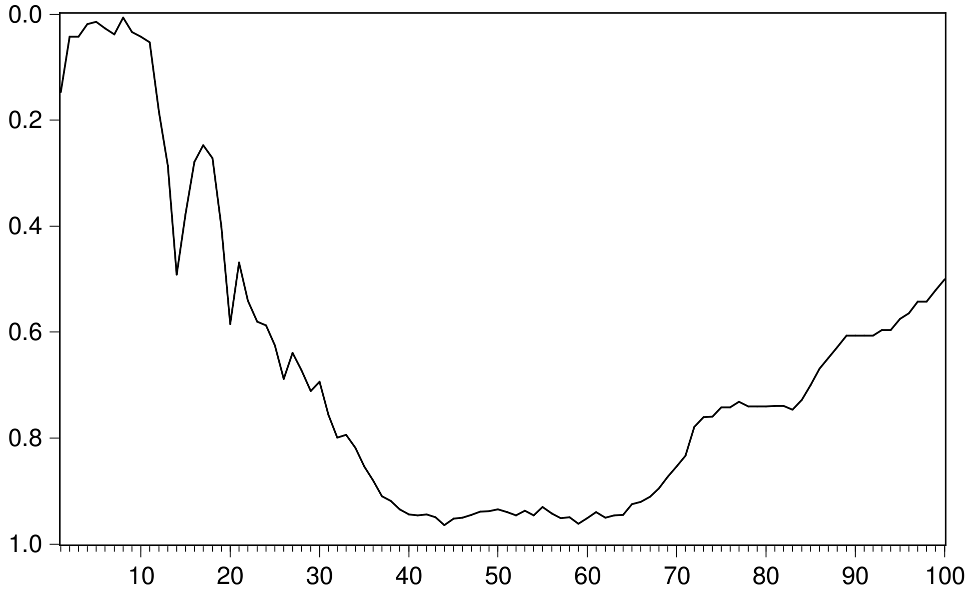
The figure shows all periods for which synchronicity f_N was higher than the full-sample average at the five percent level of significance. The left axis indicates by how much synchronicity was elevated, while the bottom axis indicates over which time period this was the case. The right axis indicates the level of the US stock market index (gray line).

Figure 4.9. Probability of constant synchronicity of Western countries with the region for all potential crisis quantiles during 2006–2008



The bottom axis indicates the percentage of extreme negative returns included in the crisis quantile, while the (inverted) left axis indicates the probability that synchronicity f_{iN} for this crisis quantile was equal to its full-sample average.

Figure 4.10. Probability of constant synchronicity within the Western region for all potential crisis quantiles during 2006–2008



The bottom axis indicates the percentage of extreme negative returns included in the crisis quantile, while the (inverted) left axis indicates the probability that synchronicity f_N for this crisis quantile was equal to its full-sample average.

4.4 Conclusion

In this chapter we examine how conclusions about stock market contagion during the 1996–1998 Asian crisis and the 2007–2009 Global Financial Crisis depend on the choice of the 'crisis' sample. To this end, we extend the synchronicity measure of Morck, Yeung, and Yu (2000) and apply it to international stock markets. The synchronicity measure does not require standardisation of the market returns, which can give results that are difficult to interpret when market returns are non-normal or heteroscedastic. In addition, we show that the synchronicity measure can easily be applied to a larger group of countries without having to define the 'source' of any contagion effects, while it can be calculated for crisis samples as small as a single trading day.

Our empirical results allow us to make a number of observations. First, choosing one country to be the 'source' of any contagion effects seems relatively restrictive. This is most clear for the 1997 Asian crisis, where synchronicity of individual countries with respect to Hong Kong, which is traditionally assumed to be the source of any contagion effects, is never significantly elevated during the crisis period identified by Forbes and Rigobon (2002). For the 2007 Global Financial Crisis, a few countries experience elevated synchronicity with the United States during the month following the collapse of Lehman Brothers, but for most countries such an effect is absent. We therefore relax the assumption of choosing a source country, and focus on synchronicity of individual countries with the rest of the region. We also analyse synchronicity within the region as a whole, where all countries are given equal weights.

Second, we find that focusing on a predefined subset of trading days is quite restrictive as well. To arrive at this conclusion we examine the approach of Forbes and Rigobon (2002), who focus on a crisis period with a given length and starting date, and the approach by Bae, Karolyi, and Stulz (2003), who focus on a crisis quantile with negative market returns lower than a given threshold. When we examine crisis periods of all possible lengths and starting dates, and crisis quantiles for all possible threshold values, we find several sub-samples for which synchronicity was higher than the full-sample average. These sub-samples differ across countries, however, and are not associated with particular crisis events or with particular threshold values for extreme stock market returns.

Our results show that contagion is a phenomenon more heterogeneous than already acknowledged in the literature. While it is common practice to report results for co-movement with a predefined source country and during a predefined crisis period or quantile, we find many 'source' countries and 'crisis' periods or quantiles for which co-movement is significantly elevated. These sub-samples cannot be related to particular crisis events or extreme return thresholds, suggesting that stock market fluctuations during financial crises are not especially contagious. Studying the determinants of increases in co-movement might contribute to identifying contagion effects, and is a fruitful avenue for future research.

Chapter 5

Contagion from Bank Defaults*

* This chapter is based on Mink (2010).

5.1 Introduction

"The provision of [...] liquidity support undermines the efficient pricing of risk by providing *ex post* insurance for risky behaviour. That encourages excessive risk-taking, and sows the seeds of a future financial crisis." Mervyn King, Governor of the Bank of England, made this statement on 12 September 2007, only two days before he had to grant emergency liquidity assistance to Northern Rock. Ever since, fiscal and monetary authorities all over the world have engaged in massive rescue operations aimed at stabilising the global financial system. These rescue operations not only made use of conventional policy instruments such as the provision of emergency liquidity assistance, but also involved extending deposit guarantee schemes, insuring or purchasing 'troubled' assets, providing capital injections, and even nationalising financial intermediaries (BIS 2009).

Fiscal and monetary authorities not only engaged in these rescue operations to protect (retail) depositors, but also to avoid contagion (BIS 2009, p. 24). Fears of contagion were based on the belief that the insolvency of one financial intermediary can have a destabilising impact on other intermediaries as well, which might destabilise the financial system as a whole and thereby disrupt the functioning of the real economy (De Bandt and Hartmann 2002). Avoiding these destabilising effects was the main motivation for the US government to rescue investment bank Bear Stearns and insurance company AIG, since the contagion effects that could be triggered by these companies' bankruptcies were believed to be particularly large (see Bernanke 2008, Federal Reserve Board 2008). Both cases illustrate how the 2007 Global Financial Crisis led financial regulators to become increasingly concerned with preventing contagion from the failure of so-called 'systemically important' financial institutions (see IMF 2009, Brunnermeier, Crockett, Goodhart, Persaud, and Shin 2009).

The recent empirical literature on contagion has focused on the banking sector, and various studies confirm that banks tend to become unstable simultaneously.[1] However, the fact that distress situations coincide across banks does not imply that there

[1] Examples are Lehar (2005), Hartmann, Straetmans, and De Vries (2006), Gropp, Lo Duca, and Vesala (2009), and Zhou (2009), who focus on correlation between returns in the tail of the distribution. Elsinger, Lehar, and Summer (2006), Adrian and Brunnermeier (2008), and Tarashev, Borio, and Tsatsaronis (2009) calculate measures of risk in the financial system as a whole, and decompose these into the contributions of individual banks.

was contagion between them, with instability of one bank *causing* the instability of another. The coincidence can also be the result of common shocks hitting banks with similar balance sheets, for instance because they all invested in the American housing market, or have similar funding structures (see also Chapter 2). Indeed, Calomiris and Mason (1997) conclude that "failures during the [1932 Chicago bank] panic reflected the relative weakness of failing banks in the face of a common asset value shock rather than contagion". Likewise, Wall and Peterson (1990) find little evidence to support the concerns about bank runs around the 1984 Continental Illinois default. Similarly, Aharony and Swary (1983) find that large bank failures only have an impact on other banks' stock prices when they are caused by problems whose revelation is correlated across banks, but not when the default is due to bank-specific factors such as internal fraud. Kho, Lee, and Stulz (2000) show that markets distinguish between exposed and non-exposed banks during a crisis, with losses of the exposed banks not spilling over to the unexposed ones. Finally, Furfine (2003), Upper and Worms (2004), and Van Lelyveld and Liedorp (2006) focus on direct exposures in the market for interbank loans, and find that the potential for contagion is rather limited.

These rejections of the contagion hypothesis seem to be at odds with policymakers' concerns as described above. Therefore, this chapter aims to disentangle the impact of contagion and common shocks on banks' market values during the Global Financial Crisis of 2007–2009. Our identification strategy is based on the presumption that if financial markets expect a bank's default to be contagious, as implied by the contagion hypothesis, an increase in their assessment of this bank's default probability should lead to a decline in other banks' market valuations. For a global sample of the one hundred largest banks, we therefore regress changes in banks' stock market values on changes in other banks' default risk. Since this analysis yields virtually no evidence for interbank contagion, it suggests that financial markets expect this risk to be of minor importance compared to the impact of adverse common shocks hitting multiple banks at the same time.

The remainder of this chapter is organised as follows. Section 5.2 introduces our method to model and estimate bank contagion, Section 5.3 describes the data used in the empirical analysis, and Section 5.4 presents our results. The final section concludes.

5.2 Method

5.2.1 Modeling bank contagion

There are several channels through which the default of one bank can cause otherwise healthy banks to suffer losses as well. The first, classic contagion channel is the interconnectedness between banks, for instance through loan and derivative exposures. An insolvent bank that defaults on its obligations will cause losses to other banks (see Allen and Gale 2000, Freixas, Parigi, and Rochet 2000). Second, Wagner (2010b) and Brunnermeier, Crockett, Goodhart, Persaud, and Shin (2009) describe how an outflow of funds can force one bank to engage in a fire sale of assets. Especially for illiquid assets such fire sales will depress market prices, which via mark-to-market accounting has to be reflected by write-downs on the value of similar assets on other banks' balance sheets. Third, contagion can arise from the opacity of banks' balance sheets, which requires investors to evaluate the value of their own bank's assets using public signals about the assets of other banks. One bank's default can this way trigger a run on other banks as well, with liquidity shortages and losses as a consequence (see Diamond and Dybvig 1983, Chen 1999).

The actual losses stemming from these contagion effects are hard to measure empirically, not the least because government rescue operations render defaults of large, potentially systemic banks a rarely observed phenomenon. We can however examine financial market data to measure the *expected* losses from contagion. If financial markets expect one bank's default to cause losses for other banks as well, an increase in their assessment of this bank's default probability should lower market valuations of these other banks. The reduction in these other banks' market valuation reflects the change in the expected value of contagious losses from all channels outlined above, including market players' expectations of any domino and feedback effects between banks.

Based on the above considerations we model the change in a bank's market value at time t as

$$y_{nt} = \alpha_n + \beta_n f_t + \sum_{m \neq n} \gamma_m p_{mt} + \epsilon_{nt}, \tag{5.1}$$

where y_{nt} denotes the change in bank n's stock market valuation at time t with $n \in$

$(1, N)$ and $t \in (1, T)$, f_t indicates the market factor, p_{mt} equals the probability that bank m will default in the future, and ϵ_{nt} captures idiosyncratic factors driving bank n's market value. When there is no contagion, the model relates the change in bank n's market value to a constant α_n and a market factor f_t, in line with the capital asset pricing model. The parameter β_n indicates to what extent changes in the market value of bank n are driven by the common market factor, causing these changes to be *correlated* with market value changes of bank m and others. The parameter γ_m indicates to what extent changes in banks' market value are *caused* by changes in bank m's default risk, taking the effect of contagion into account. If the default of a bank m would cause contagious losses for other banks, parameter γ_m will be negative since an increase in p_m then leads markets to price the higher expected value of these losses, causing market value y_{nt} to decline.[2]

Equation (5.1) makes clear that even when no actual bank defaults occur, we can still examine the impact of contagion on banks' market values. This is the case because forward-looking markets price the expected costs of potential future bank defaults, by responding to changes in these banks' default probabilities. Since these default probabilities and the changes therein are close to zero in normal times and only become substantial during financial crises, our empirical model is in line with the contagion definition by Forbes and Rigobon (2002), who focus on increased shock transmission during periods of crisis (see also Chapter 3). While Forbes and Rigobon (2002) model contagion as a sudden increase in the parameter β_n during such periods, with the challenge being to distinguish this parameter instability from an increase in the variance of the unobserved market factor f_t, we model contagion as the impact of a sudden increase in the variable p_m. When financial markets incorporate information about such default probabilities into other banks' market valuations, increasing bank default probabilities can lead to parallel declines in stock prices similar to the ones analysed by Forbes and Rigobon (2002).

[2] We assume the impact of contagion from bank m is the same across all N banks on the left-hand-side of the regression equation. This restriction is necessary to reduce the number of contagion parameters to be estimated, which would otherwise increase from N to $N(N-1)$. As a result, the parameter estimates will pick up contagion from banks who are truly 'systemically important', i.e. whose failure would have an impact on multiple banks at the same time.

5.2.2 Estimating bank contagion

In matrix notation, for the tth observation, the model in Equation (5.1) can be written as

$$y_t = \alpha + \beta f_t + \Gamma p_t + \epsilon_t, \tag{5.2}$$

where y_t is an $N \times 1$ vector of changes in banks' market values, Γ is the $N \times N$ matrix equal to $\iota_N \gamma'$ but with diagonal elements replaced by zeros, and ι_N is an N-vector of ones and $\gamma \equiv (\gamma_1, ..., \gamma_N)'$. To write this model in the usual regression format we rewrite Γp_t as $A_t \gamma$, where $A_t = \iota_n p_t' - \text{diag}(p_t)$. The entire model is now

$$y = (\iota_T \otimes I_N)\, \alpha + f \otimes \beta + A\gamma + \epsilon, \tag{5.3}$$

with A the $NT \times T$ matrix of all the A_t's stacked on top of each other. Equation (5.3) is a standard panel regression equation, apart from the unknown factor $f \equiv (f_t, ..., f_T)'$. We estimate this factor as the coefficient vector from the regression

$$r = Df + \eta, \tag{5.4}$$

where r is the residual vector for the regression of y on $(\iota_T \otimes I_N)$ and A. The $NT \times T$ matrix D consists of all $N \times T$ matrices D_t stacked on top of each other, where D_t is a matrix of zeros with ones on the tth column.

To estimate the model we apply a three-step approach. First, we regress bank market values y_t on a set of bank fixed effects and default probabilities p_t. Second, we regress the residuals r_t from this regression on a set of period fixed effects to obtain the market factor f.[3] Finally, we add this market factor as an explanatory variable to the first-step regression and re-estimate this regression to obtain the model coefficients in Equation (5.1). We calculate confidence bounds around these coefficients using a standard bootstrap procedure. In particular, we resample the residuals within cross-sections and repeat the three estimation steps for 1000 bootstrap replications, using the

[3] We estimating the market factor from the first-step residuals r rather than from the market values y to make sure it is orthogonal to the default probabilities. This way we avoid the market factor to pick up any common variation across market values that should have been attributed to changes in bank default probabilities. However, this approach does introduce the risk that the estimated contagion coefficients pick up some of the effects of the market factor, which would lead us to overestimate them.

dispersion of coefficient estimates to construct 95-percent confidence intervals.[4]

5.3 Data

We calculate changes in market values as the change in the value of banks' outstanding equity, while we use changes in banks' credit default swap (CDS) spreads as indicators of changes in their default risk. CDS-spreads have the advantage that they are directly observed in financial markets. Moreover, they have been widely used as indicators of default risk by practitioners, policy makers and academics alike. A caveat associated with using these spreads is that they do not purely measure a bank's expected probability of default, but indicate the percentage premium to be paid for an insurance against the risk that bank m does not repay its outstanding debt in full. The spread therefore is also a function of the losses on bank m's debt given that it defaults, and of the risk that the writer of the CDS-contract defaults himself.

As an alternative to using CDS-spreads as indicators of bank default risk, we follow Crosbie and Bohn (2003) and calculate probabilities of default by mapping banks' distances to default to the cumulative density function of the standard normal distribution. While calculating the distance to default requires several variables as inputs that are not observed on a high-frequency basis, Byström (2006) shows that especially for banks, the distance to default can be approximated by the inverse of the expected volatility of equity returns.[5] We thus calculate the probability of default as

$$p_{mt} = \mathcal{N}\left(-1/\sigma_{m,t+1}\right), \tag{5.5}$$

where $\sigma_{m,t+1}$ equals the standard deviation of equity returns at time $t+1$. We calculate

[4] The estimates of the contagion coefficients are not affected by government bailouts of bank m, since the observed fluctuations in bank m's CDS-spread or default probability are already conditional upon the prospect of such rescue operations taking place. Also potential government guarantees for bank i are unlikely to affect our results. These guarantees are after all designed to shield bank i's bondholders from losses, but do not aim to protect the bank's shareholders. See also King (2009). Finally, the contagion coefficients could in theory be underestimated due to governments intending to mitigate the contagious impact of bank m's default through for instance providing additional liquidity to the system or buying troubled assets. Changes in the prospect of such mitigating measures would however drive market values and CDS-spreads in opposite directions. As this inverse relationship is also implied by the contagion hypothesis, the omission of such changes from our regression equation could just as well cause contagion coefficients to be overestimated.

[5] Using equity volatility as a measure of default risk is quite common in the literature, see for instance Saunders, Strock, and Travlos (1990), Esty (1998), González (2005), Stiroh (2006) and Laeven and Levine (2010).

$\sigma_{m,t+1}$ as the one-period ahead forecast from a GARCH(1,1) model fitted to weekly logarithmic equity returns.[6] In this way we can infer changes in banks' market values y as well as in their default probabilities p directly from stock market data.[7]

We obtain data on banks' stock market values between January 1st 2007 and December 31st 2009 from Thomson Datastream.[8] Table 5.1 reports the 96 banks that we include in the analysis, of which 26 are located in the United States and 70 are from countries in the European Union. Our selection of banks covers the largest part of these regions' banking systems. We calculate y as the weekly change in these banks' stock market values, expressed in local currencies (see Chapter 3). By focusing on weekly data, our analysis is less sensitive to noise in the market returns and to any time lags in the response of market values to changes in default probabilities. We obtain 5-year CDS-spreads on senior debt from Thomson Datastream for a sub-sample of 55 banks, indicated with an asterisk in Table 5.1.

Figure 5.1 shows the development over time of the cross-sectional averages of banks' market values, probabilities of default, and CDS-spreads. The graph in the top panel illustrates that banks' market values have substantially declined over the 2007–2008 period. During the second and third quarter of 2009 market values recovered somewhat, while thereafter they remained more or less stable. The graph in the middle of the figure shows the average spread on banks' CDS-contracts. Spreads started to increase from the second half of 2007 onwards, and spiked in September 2008 after the collapse of Lehman Brothers. The graph in the bottom panel shows that also probabilities of default were especially volatile around the Lehman collapse. The volatility of default probabilities underlines that default risk is absent during normal times, but

[6] We calculate the weekly logarithmic returns as the sum of absolute daily logarithmic returns, where we interpolate 0.25 percent of the daily observations to control for unexpectedly large changes in volatility (as would result from sudden capital injections). The days for which we interpolated the data were selected as those for which fitting a GARCH(1,1)-model yielded the largest standardised residual.

[7] In the Appendix we show that this approach to calculate the distance to default yields results which are highly similar to the original approach suggested by Crosbie and Bohn (2003).

[8] We select banks that are classified as Bank Holding & Holding Companies, Commercial Banks, Cooperative Banks, Investment Banks, Real Estate/Mortgage Banks, and Savings Banks, with leverage $D/(D+V)$ at least equal to 0.85 by the end of 2006 (where D equals the book value of debt and V equals the market value of the equity). We also keep Bank of America, whose leverage by the end of 2006 equals 0.847. We limit the set of countries to the EU-15, Iceland, Norway, Switzerland, and the United States, and remove banks from the sample for which shares were not actively traded during all trading days of January 2007. Finally, we exclude Bank Austria Creditanstalt and Bayrische Hypo- und Vereinsbank (both part of UniCredit), Banca Lombarda (part of UBI Banca), BHW Holding (part of Deutsche Postbank), Depfa bank (part of Hypo Real Estate), Commerce Bancorp (part of TD bank), and Banca CR Firenze (largely owned by Intesa Sanpaolo).

Table 5.1. Overview of banks included in the sample

Bank	Country	Market value	Bank	Country	Market value
Citigroup*	US	207,814	Anglo Irish Bank Corporation (until 15/01/2009)*	IE	11,333
Bank of America*	US	182,048	Deutsche Postbank*	DE	10,453
HSBC Holdings*	GB	160,442	Banco de Sabadell	ES	10,377
JP Morgan Chase & Co.*	US	127,221	Banco Comercial Português*	PT	10,112
UBS*	CH	97,002	Crédit Industriel et Commercial (CIC)	FR	10,096
Royal Bank of Scotland Group*	GB	93,459	Sovereign Bancorp (old) (until 30/01/2009)	US	9,117
Banco Santander*	ES	88,436	CIT Group (until 01/11/2009)*	US	8,397
BNP Paribas*	FR	76,903	Banco Popolare	IT	8,163
ING Groep*	NL	74,067	LBB Holding (Landesbank Berlin Holding)	DE	7,955
Barclays*	GB	71,045	Eurohypo (until 25/07/2008)	DE	7,714
UniCredit*	IT	69,161	Alliance & Leicester (until 13/10/2008)*	GB	7,422
Wachovia (until 29/09/2008)*	US	68,374	Northern Rock (until 18/02/2008)*	GB	7,389
Morgan Stanley*	US	64,852	UBI Banca	IT	7,172
Banco Bilbao Vizcaya Argentaria	ES	64,788	Comerica Incorporated	US	7,078
Goldman Sachs Group*	US	64,457	Banco Espirito Santo*	PT	6,810
Credit Suisse Group*	CH	64,401	Kaupthing Bank (until 06/10/2008)*	IS	6,597
HBOS (until 13/10/2008)*	GB	63,405	Swiss Life Holding	CH	6,416
Merrill Lynch & Co. (until 05/12/2008)*	US	62,300	Hypo Real Estate Holding (until 06/10/2008)	DE	6,391
Société Générale*	FR	59,288	Banca Popolare di Milano*	IT	5,458
Deutsche Bank*	DE	52,962	Bankinter	ES	4,644
Lloyds Banking Group*	GB	47,939	Banco BPI	PT	4,492
Crédit Agricole*	FR	47,705	Bradford & Bingley (until 29/09/2008)*	GB	4,443
ABN Amro Holding (until 25/04/2008)*	NL	47,162	Banca popolare dell'Emilia Romagna	IT	4,352
Fannie Mae (until 07/09/2008)	US	43,970	Huntington Bancshares	US	4,285
Fortis (until 04/10/2008)*	BE	42,117	First Horizon National Corporation	US	3,949
Freddie Mac (until 07/09/2008)	US	35,776	Banco Pastor	ES	3,860
Metlife*	US	34,063	SNS Reaal	NL	3,857
KBC Group	BE	34,054	Investec	GB	3,722
Washington Mutual (until 26/09/2008)	US	32,649	Banca Italease (until 09/11/2009)	IT	3,691
Prudential Financial*	US	31,619	Glitnir Bank (until 06/10/2008)*	IS	3,569
Lehman Brothers Holdings (until 15/09/2008)*	US	31,441	Jyske Bank (Group)	DK	3,334
Standard Chartered*	GB	30,767	Landsbanki (until 06/10/2008)*	IS	3,136
Nordea Bank*	SE	30,273	Emporiki Bank of Greece	GR	3,085
Natixis*	FR	25,912	CREDEM	IT	3,017
Dexia*	BE	23,839	IKB Deutsche Industriebank*	DE	2,576
Danske Bank*	DK	23,525	Sydbank	DK	2,535
Countrywide Financial Corporation (Old) (until 11/01/2008)*	US	20,019	IndyMac Bancorp (until 11/07/2008)	US	2,430
Allied Irish Banks*	IE	19,828	Astoria Financial Corporation	US	2,270
Commerzbank*	DE	18,894	Pohjola Bank	FI	2,024
Erste Group Bank	AT	18,319	Credito Bergamasco	IT	1,870
Bank of Ireland*	IE	17,076	Wüstenrot & Württembergische	DE	1,738
Skandinaviska Enskilda Banken*	SE	15,951	Downey Financial (until 21/11/2008)	US	1,535
Svenska Handelsbanken*	SE	14,585	South Financial Group	US	1,519
Bear Stearns Companies (until 17/03/2008)*	US	14,500	Aareal Bank	DE	1,507
DnB Nor	NO	14,362	Valiant Holding	CH	1,415
Swedbank*	SE	14,166	First Citizens BancShares	US	1,347
Banca Monte dei Paschi di Siena*	IT	12,031	BANIF SGPS	PT	1,325
BANESTO*	ES	11,637	UCBH Holdings (until 06/11/2009)	US	1,261

Note: market values refer to the value of banks' equity by the end of 2006, reported in millions of euro; an asterisk indicates data on CDS-spreads is available.

can become quite real during times of crisis. In general, although both start to increase around mid-2007 and on several occasions peak simultaneously, the reported default probabilities differ substantially from the observed CDS-spreads. The differences between both indicators probably reflect that they measure somewhat different concepts, consider different time horizons, and are calculated for different samples of banks. Moreover, Stulz (2010) shows that CDS-contracts are generally traded over the counter instead of on public exchanges, so that data on these spreads are likely to be somewhat noisy. Because of these differences we use both CDS-spreads and model-based default probabilities in our regression analysis, as both are popular indicators of default risk in the literature.

Table 5.2 reports bivariate correlations between the variables included in the regression model. First, the top two rows show that the average correlation between changes in a bank's market value and changes in its CDS-spread is smaller than zero, while correlation between changes in market values and changes in default probabilities is close to zero. The difference between both could be due to the fact that for instance changes in investor risk aversion drive market values and CDS-spreads in opposite directions, while they do not directly affect the probability of default. Such changes in risk aversion might cause us to overestimate any contagion effects, as these effects also imply a negative correlation between market values and CDS-spreads. The next two rows show that the correlation between changes in default probabilities and between changes in CDS-spreads is generally low, so that collinearity between our default risk variables is unlikely to be a problem. Finally, the last row shows that changes in default probabilities and CDS-spreads on average are virtually uncorrelated. Although both measures are popular indicators of default risk, they apparently capture different aspects thereof.

5.4 Results

5.4.1 Main results

Table 5.3 reports the results from estimating the regression model in Equations (5.3) and (5.4). To facilitate the interpretation of the coefficients, we divide each variable in

Figure 5.1. Cross-sectional averages of bank market values, CDS-spreads and probabilities of default

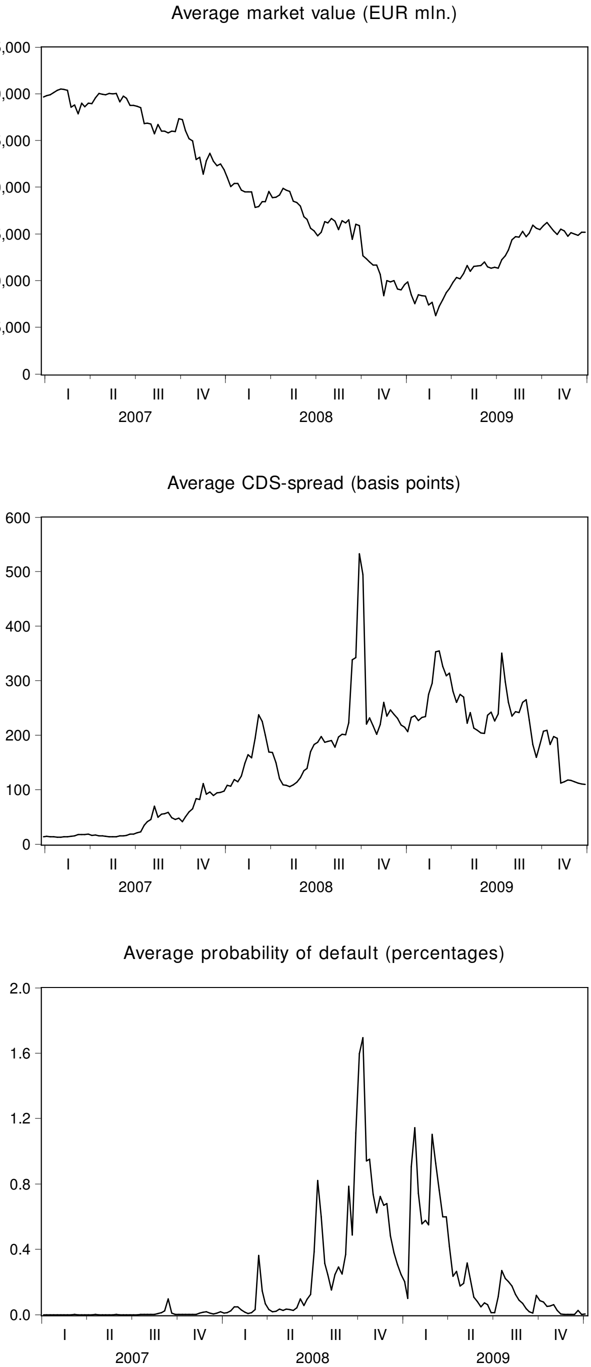


Table 5.2. Correlation between the regression variables

	Minimum	Average	Maximum
$\mathrm{Cor}(y_i, cds_i)$	-0.81	-0.32	0.04
$\mathrm{Cor}(y_i, p_i)$	-0.85	-0.02	0.68
$\mathrm{Cor}(cds_i, cds_j)$	-0.62	0.39	0.97
$\mathrm{Cor}(p_i, p_j)$	-0.71	0.12	1.00
$\mathrm{Cor}(p_i, cds_i)$	-0.38	0.04	0.97

Note: y_i, p_i and cds_i denote the time series with changes in bank i's market value, stock-price based default probability, and CDS-spread.

the model by its standard deviation before estimating the regression, so that each coefficient indicates the regressor's correlation with the dependent variable. This transformation avoids our coefficient estimates from being predominantly driven by the large banks in the sample, whose changes in market values would otherwise account for a large part of the variation in the dependent variable. By doing so we focus on the impact of contagion on the system of banks as a whole, rather than on a smaller subset thereof.

The first row in the top panel reports the results for the regression with CDS-spreads as indicators of bank default risk. The first entry shows that in the full sample of banks, the cross-section average of the estimated constants α_n equals -0.04. The next entry shows that these estimates are for only 7 percent of the banks significantly smaller than zero (at the five-percent level). The second pair of entries shows that the common shock coefficient on average equals 0.34, and is significantly larger than zero for 95 percent of the banks in the sample. Even though the banks in the sample are fairly different from each other, common shocks are thus an important driving force of changes in their market values. This result implies that changes in bank market values are correlated amongst each other also when there is no contagion.

The entries in the next three columns of the table focus on the contagion effect, i.e. the impact that changes in banks' default risk have on other banks' market values. This impact turns out to be limited, as the average γ_m coefficient is close to zero with a value of -0.01. For 35 percent of the banks, the estimated contagion coefficient is

Table 5.3. Estimation results

Regression equation: $y_{nt} = \alpha_n + \beta_n f_t + \sum_{m \neq n} \gamma_m p_{mt} + \epsilon_{nt}$

Model with CDS-spreads	Constant		Common shocks		Contagion				
	α_n	$\alpha_n < 0$	β_n	$\beta_n > 0$	γ_m	$\gamma_m < 0$	$\gamma_m > 0$	R^2	N
Full sample	-0.04	7 %	0.34	95 %	-0.01	35 %	20 %	0.36	13399
Sub-samples based on location									
n and m all from US	-0.12	46 %	0.53	100 %	-0.04	38 %	23 %	0.49	3284
n and m all from EU	-0.03	7 %	0.44	97 %	-0.02	33 %	19 %	0.40	10115
Sub-samples based on size									
n and m all large	-0.04	8 %	0.43	100 %	-0.02	29 %	22 %	0.47	6724
n and m all small	-0.06	17 %	0.42	100 %	-0.03	71 %	14 %	0.29	6675

Model with default probabilities	Constant		Common shocks		Contagion				
	α_n	$\alpha_n < 0$	β_n	$\beta_n > 0$	γ_m	$\gamma_m < 0$	$\gamma_m > 0$	R^2	N
Full sample	-0.06	16 %	0.43	100 %	-0.01	25 %	20 %	0.37	13399
Sub-samples based on location									
n and m all from US	-0.13	50 %	0.60	100 %	0.00	35 %	31 %	0.49	3284
n and m all from EU	-0.05	13 %	0.49	100 %	-0.01	26 %	17 %	0.41	10115
Sub-samples based on size									
n and m all large	-0.05	15 %	0.55	100 %	-0.01	31 %	17 %	0.48	6724
n and m all small	-0.07	21 %	0.43	100 %	-0.01	25 %	19 %	0.30	6675

Note: 'large' bank are banks with the 50 percent highest market values at the end of 2006, which are reported in the left column of Table 5.1. The other 50 percent of the banks are considered to be 'small'. All variables have been divided by their standard deviations before estimating the regression. Percentages in the table indicate the fraction of banks for which the regression coefficient was statistically larger/smaller than zero at the 5 percent significance level.

significantly negative, while we find significantly positive coefficients for 20 percent of the banks examined. In these cases, the sign of the coefficient estimate is opposite to what would be predicted by the contagion hypothesis. The next column shows that the R-squared of the regression equals 0.36. The last column reports the number of observations included in the regression.

The results for the full sample indicate that banks' exposure to the market factor is much larger than their exposure to changes in each other's default risk. To examine this result in more detail, the next rows in the top panel of the table focus on the coefficient estimates for several sub-samples of banks. The second and third rows report coefficient estimates for sub-samples based on location, distinguishing between banks located in the US and banks located in the EU. We expect banks in the same region to be more exposed to common shocks than banks from different regions. In addition, IMF (2009) argues that banks that are more interconnected are also more likely to suffer from contagion when one of them goes bankrupt. To the extent that banks from the same region are more interconnected, we expect contagion between them to be higher as well.

The results show that banks that either are all from the US or are all from the EU are indeed more exposed to common shocks. That is, the β_n coefficient estimated for US banks using a US market factor equals 0.53 on average, while for the EU this value equals 0.44. Both values are higher than the corresponding value of 0.34 estimated for the full sample. This result also shows that the correlation between banks via the market factor is stronger in the US than in the EU, illustrating that Europe is more heterogeneous. The contagion coefficient for both sub-samples is close to zero, equalling -0.04 for the US and -0.02 for the EU. In addition, the percentages of significantly positive and negative contagion coefficients are comparable to those found for the full-sample regression.

The last two rows in the top panel focus on sub-samples based on banks' size. We distinguish between the fifty percent largest banks in the sample, included in the left column of Table 5.1, and the fifty percent smallest banks. Amongst others, IMF (2009) argues that especially the failure of large banks has a contagious impact on other banks in the system. The results in the table do not provide any evidence for such an effect: the coefficient estimates for the contagion effect are close to zero. For smaller banks they are significantly negative in 71 percent of the cases, but still the results strengthen our finding that contagion effects are of only limited importance as driving forces of banks' market values.

A possible explanation for the rather small contagion effects in the regressions with CDS-spreads, is that these spreads are inaccurate measures of banks' default risk. To examine this possibility in more detail, the lower panel in the table reports the regression results obtained when using changes in default probabilities inferred from stock price data as indicators of banks' default risk. While CDS-spreads are only available for a sub-set of 55 banks, the stock market based default probabilities are available for all 96 banks in the sample. The first row of the panel shows that the common shock coefficient on average is higher than for the regression using CDS-spreads, indicating that the CDS-spreads pick up some of the variation that should actually be attributed to the market factor. The contagion coefficient is still close to zero, and is significantly smaller than zero for only 25 percent of the banks in the sample. The R-squared of the regression is about the same as the corresponding one in the top panel of the table.

The next rows in the table confirm the results from the CDS-spread regressions. The common shock coefficients are higher than the estimates in the top panel., and again suggest that larger banks are more homogeneous. This result is in line with the intuition that larger (universal) banks tend to engage in a similar, diversified range of activities, while smaller (specialised) banks tend to be more active in local niche markets (in line with the model in Chapter 2). On average, the contagion coefficients for all sub-samples are close to zero, and even exactly zero for US banks. The R-squared values from the regressions are about the same as before.

We have shown that financial markets expect the contagious impact from the default of an individual bank m to be fairly small, which holds both for regressions using default probabilities as well as regressions using CDS-spreads as indicators of bankruptcy risk, and for regressions focusing on sub-samples based on banks' location as well as size. Still, a caveat from the analysis is that we estimate coefficients for contagion from individual banks. While these coefficients are close to zero, it could be that the aggregate instability of the banking sector does have a negative impact on banks' market values. If such an effect exists, changes in banks' market values are driven by the common variation in banks' default probabilities rather than by changes in the default probabilities of individual banks. We examine this hypothesis by omitting the individual default probabilities from the regression model in Equations (5.3) and (5.4), and estimate the common market factor from changes in banks' market values, i.e. without first regressing these market values on bank default probabilities. The difference between this new estimate of the market factor and the original one, is that the new one also picks up any changes in banks' market values due to contagion from the aggregate instability of the banking sector. The average over all banks of the β_m coefficient estimated for this new market factor equals 0.58, which is higher than the original coefficients of 0.34 and 0.43 reported in Table 5.3. At the same time, the R-squared from the regression is 0.37, which is equal to the R-squareds from the original regressions. Only the common variation in banks' default probabilities has any power in explaining changes in banks' market values. As this common variation will however for an important part be driven by third factors such as changes in global investor risk aversion, the correlation of this common variation with changes in banks' market values cannot be directly attributed to any contagion effects.

5.4.2 Lehman Brothers

Our finding that interbank contagion explains only a very limited amount of banks' market value changes during the credit crisis seems to be at odds with the aftermath of the Lehman Brothers default on 15 September 2008. After this date, counterparty risk awareness spread through the financial system, with quickly rising money market interest rates as one of the results. While it seems only natural to conclude that this turmoil was caused by the default of Lehman Brothers, Taylor (2009) and Huertas (2010) argue that it was triggered by markets' uncertainty about the ability of governments to bail-out troubled financial institutions. Such safety nets play a large role in market participants' risk assessments, as was made explicit when Moody's (2007) announced that its future bank credit ratings would also incorporate the likelihood of a government rescue operation in case of an imminent default. Consequently, Icelandic banks received a five-step upgrade to a triple-A rating, which until then had been reserved for only the most solvent of financial institutions. The (threat of) removal of government safety nets can thus have a substantial impact on the market value of financial intermediaries and on the interest rates against which they can borrow funds (see also Standard & Poor's 2011). Consequently, the aftermath of the Lehman default could also be due to the common shock stemming from the signal by the US government that defaulting large banks would not necessarily be rescued.

We obtain the individual β and γ coefficients for Lehman Brothers from the regressions underlying the results in Table 5.3. Lehman's correlation with the market factor equals 0.20 for the regression with CDS-spreads and 0.53 for the regression with default probabilities, with both values being statistically significant at the 5-percent level. The contagion coefficient is 0.11 for the regression with CDS-spreads and 0.12 for the regression with default probabilities. Both are of the wrong sign, and as it turns out significantly so. These findings are in line with those reported in Table 5.3.

That market participants expected contagion from Lehman to be of minor importance could seem surprising at first. This result however is consistent with the objectives of financial regulation and supervision, which aims to minimise contagion through for instance imposing limits on large exposures to individual counterparties and investments in a single asset class, and also requires the posting of collateral to mitigate counterparty credit risk. Concerning the aftermath of the Lehman bankruptcy, BIS (2009, p.24) concludes that "Lehman-referencing CDS exposures turned out to be smaller than feared. They eventually translated into relatively modest net settlement payments of about USD 5.2 billion, which would be closed out without incident in late October." Our findings might also be due to market participants expecting governments to prevent the contagious fallout after any bank defaults. As discussed above such expectations are unlikely to fully explain our results, but if so, this would be evidence of widespread moral hazard amongst financial market players.

5.5 Conclusion

Simultaneous defaults in the banking sector are often attributed to interbank contagion, but can also be due to common shocks affecting banks with similar balance sheets. We disentangle these two effects by examining whether financial markets expected bank defaults to be contagious during the 2007–2009 Global Financial Crisis. Our strategy to identify contagion is based on the presumption that if financial markets expect one bank's default to cause other banks to suffer losses as well, as implied by the contagion hypothesis, an increase in this bank's default probability should lead to a decline in the other banks' stock market valuations. For a global sample of the one hundred largest banks, we test for contagion by regressing changes in banks' market values on changes in other banks' CDS-spreads or default probabilities. While we find changes in market values to be correlated across banks through a common market factor, a change in one bank's CDS-spread or default probability hardly affects the market's valuation of any other banks in the sample.

Our findings suggests that financial market participants expect contagion risk to be of minor importance compared to the impact of common adverse shocks affecting the banking sector as a whole. Whether these expectations are correct or not, the fact that contagion risk does not seem to be priced implies that the simultaneous declines in banks' market values have been primarily due to common shocks affecting banks with similar exposures to the economic and political environment. Examples of such shocks are a decline in U.S. house prices, a global recession, a change in monetary policy, or a change in governments' willingness to bailout troubled financial institutions. While financial market dynamics such as herding can amplify the impact of such shocks on the financial system, our results show that these shocks or the amplification thereof are not driven by changes in the default risk of individual banks. This finding is in line with earlier literature showing that common shocks rather than contagion are the main drivers of banking sector instability.

5.A Appendix

Crosbie and Bohn (2003) show that a bank's probability of default PD can be calculated as

$$PD = \mathcal{N}\left(-DD\right) = \mathcal{N}\left(-\frac{\ln\left(V_A/D\right) + \left(\mu - 0.5\sigma_A^2\right)T}{\sigma_A\sqrt{T}}\right), \tag{5.6}$$

where $\mathcal{N}\left(\cdot\right)$ denotes the standard normal cumulative probability distribution. The probability of default is a function of the distance to default DD, which indicates the expected number of standard deviations that the bank is away from the point where its asset value is insufficient to cover its liabilities at the time these become due. This distance is a function of the market value of the bank's assets V_A, the expected return on assets μ, this return's standard deviation σ_A, the book value of debt D, and this debt's maturity T. To obtain the market value of assets, Crosbie and Bohn (2003) use the option pricing framework of Black and Scholes (1973) and Merton (1974), which links V_A to the market value of equity V as

$$V = V_A\mathcal{N}\left(d_1\right) - e^{-rT}D\mathcal{N}\left(d_1 - \sigma_A\sqrt{T}\right), \tag{5.7}$$

with $d_1 = \frac{\ln(V_A/D)+\left(r+0.5\sigma_A^2\right)T}{\sigma_A\sqrt{T}}$ and r being the risk-free interest rate. The standard deviation of expected future asset returns σ_A can be related to the standard deviation of expected future equity returns σ via

$$\sigma = \frac{V_A}{V}\mathcal{N}\left(d_1\right)\sigma_A. \tag{5.8}$$

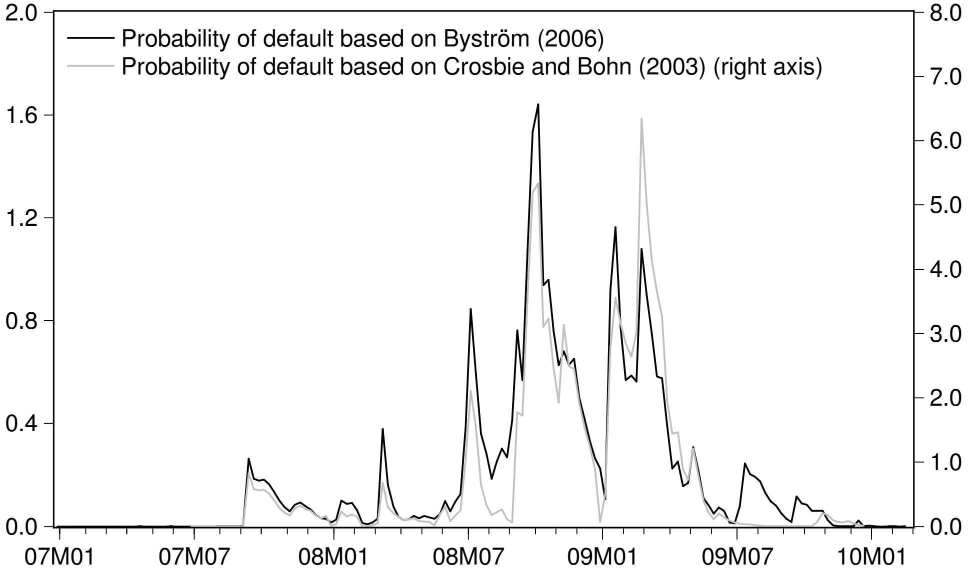
While it provides an internally consistent approach to derive the probability of default PD, solving the above system of Equations (5.6)-(5.8) requires data on D, T, r, and μ, which are notoriously difficult to obtain especially on a high-frequency basis (we cannot use ex-post statistics since market participants did not have these available when they engaged in the trading decisions leading to the observed values for V and σ). Book values of debt D are only reported once a year in banks' annual reports, and are generally not itemised to different maturities T. In practice, D is often set equal to the sum of interpolated short-term debt and fifty percent of interpolated long-term debt, while it is assumed that this total amount has a homogeneous maturity structure

T of one year. Risk-free interest rates r only exist in theory and are often approximated by the return on U.S. Treasury Bills, whereas expected future asset returns μ are constructed by extrapolating historical asset returns using a moving average of several months (see for instance Vassalou and Xing 2004, Duffie, Saita, and Wang 2007). These approximations are quite crude, and are unlikely to reflect the actual beliefs of market participants regarding for instance the risk-free interest rate during crisis interventions by the Federal Reserve, or the debt maturity structure and future asset returns of Lehman Brothers' just before this institution went bankrupt.

In light of these data limitations, we follow Byström (2006) and use stock market data to calculate the distance to default as $DD = 1/\sigma$. We estimate σ as the forecast from a GARCH model fitted to the time series of logarithmic equity returns. Byström (2006) finds that this measure is equal to the distance to default implied by CreditGrades, a structural model to calculate credit spreads that was introduced by the risk management firm RiskMetrics in 2002, and was endorsed by Deutsche Bank, Goldman Sachs, and JP Morgan. Moreover, he shows that especially for highly levered firms such as banks, $1/\sigma$ closely approximates the distance to default in Equation (5.6). As our approximation has the same $z-$score functional form as the original distance to default, which Bharath and Shumway (2008) show is the main driving force behind this measure's ability to forecast actual bankruptcies, we can map it to the standard normal distribution to obtain the default probability PD. Figure 5.2 shows that the resulting probabilities of default are similar to the ones implied by Equation (5.6).[9]

[9] We calculate the Merton (1974) distance to default using the same approach as Vassalou and Xing (2004) and Duffie, Saita, and Wang (2007), setting D equal to short-term debt and fifty percent of long-term debt (obtained from Datastream and interpolated to a weekly frequency), setting r equal to the return on U.S. Treasury Bills obtained from the Federal Reserve Board, and calculating μ as the six-month moving average of logarithmic asset returns. For equity volatility σ we use the GARCH estimates discussed above.

Figure 5.2. Cross-sectional averages of probabilities of default based on Byström (2006) and on Crosbie and Bohn (2003)



Chapter 6

Contagion from Country Defaults*

[*] This chapter is based on Mink and de Haan (2012).

6.1 Introduction

In the course of 2010, the financial problems of Greece became so severe that the euro countries agreed to provide bilateral loans for a total amount of EUR 80 billion to be disbursed over the period May 2010 through June 2013. In addition, the International Monetary Fund (IMF) financed EUR 30 billion under a stand-by arrangement. An important motivation to provide financial support to Greece despite the no-bailout clause in the Maastricht Treaty was fear of contagion, see for instance ECB Vice-president Constâncio (2011). It was feared that a restructuring of Greek debt could lead to a new banking crisis in the EU as several banks, notably in France and Germany, had a high exposure to Greece. In addition, policymakers were afraid that a Greek default would spill over to other highly indebted countries in the euro area.

The threat of contagion from a sovereign default is however not undisputed. According to Cochrane (2010), "we're told that a Greek default will threaten the financial system. But how? Greece has no millions of complex swap contracts, no obscure derivatives, no intertwined counterparties. Greece is not a brokerage or a market-maker. There isn't even any collateral to dispute or assets to seize. This isn't new finance, it's plain-vanilla sovereign debt, a game that has been going on since the Medici started lending money to Popes in the 1400s. People who lent money will lose some of it. Period." With respect to a Greek default spilling over to other countries, Cochrane argues "we're told that a Greek default will lead to 'contagion.' The only thing an investor learns about Portuguese, Spanish, and Italian finances from a Greek default is whether the EU will or won't bail them out too. Any 'contagion' here is entirely self-inflicted. If everyone knew there wouldn't be bailouts there would be no contagion."

The argument by Cochrane (2010) closely resembles the main message from research by Aharony and Swary (1983). These authors perform an event study to examine contagion to other banks when a large bank goes bankrupt. Their analysis indicates that "when the failure of a large bank is caused primarily by problems specific to the bank, such as fraud, no contagion effects are observed. When the failure of a large bank is caused by problems whose revelation is correlated across banks, the observed fall in prices of solvent bank stocks may be interpreted as investors' response to a common type of unfavourable signal, rather than a contagion effect" (p. 305). In the context of a Greek sovereign default, this 'unfavourable signal' would be the revelation that euro area governments apparently are not willing to shield private investors from losses anymore when countries are about to default on their debt obligations.

There is, as yet, surprisingly limited research on contagion in the current euro area debt crisis.[1] To identify contagion it is necessary to identify a country-specific event that affects asset prices other than the sovereign bond price of the country concerned. We adopt the standard event study approach reviewed by MacKinlay (1997) and used in earlier work on contagion by, for instance, Aharony and Swary (1983), Kho, Lee, and Stulz (2000) and Brewer III, Genay, Hunter, and Kaufman (2003). As an innovation to this approach, we identify the events as the trading days in 2010 with the largest volatility in yields on Greek government bonds and relate those days to the 'news' that caused these fluctuations. This approach circumvents a major problem of event studies, which for sovereign rating changes was most recently illustrated by Michaelidis, Milidonis, Nishiotis, and Papakyriacou (2012), namely how to identify major event days during which there is really an event that is not expected (and therefore not priced in). The news reports, taken from Reuters, were classified into two categories: news about Greek public finances and news about the willingness (or lack thereof) of European countries to provide financial support to Greece. This way we can distinguish between market reactions due to fears of contagion from a Greek default and reactions reflecting moral hazard caused by the prospect of a sovereign bailout.

In the empirical analysis, we start with examining the impact of news about Greece and its potential bailout on bank stock prices. As pointed out by Davies and Ng (2011), there are several channels through which deteriorating sovereign creditworthiness may affect banks.[2] First, increases in sovereign risk cause losses on banks' govern-

[1] Exceptions include Arezki, Candelon, and Sy (2011), Missio and Watzka (2011), Afonso, Furceri, and Gomes (2011) and De Santis (2012). Arezki, Candelon, and Sy (2011) examine the spillover effects of sovereign rating news on European financial markets during the period 2007–2010. They find that sovereign rating downgrades have statistically and economically significant spillover effects both across countries and financial markets. Downgrades to near speculative grade ratings for economies such as Greece have a systematic spillover effect across euro area countries. Missio and Watzka (2011) use a dynamic conditional correlation model (DCC) to study contagion in the euro area. Their results show that Portuguese, Spanish, Italian and Belgian yield spreads increase along with their Greek counterpart. Afonso, Furceri, and Gomes (2011) examine whether sovereign yields and CDS spreads in a given country react to rating announcements of other countries. They conclude that there is evidence of contagion, especially from lower rated countries to higher rated countries. Finally, De Santis (2012) shows sovereign bond spreads in the euro area can be decomposed into i) aggregate regional risk, ii) country-specific credit risk, and iii) spillovers from Greece.

[2] Acharya, Drechsler, and Schnabel (2011) find that after several bank bailouts in 2008, bank CDS spreads declined across all countries with a corresponding increase in sovereign CDS spreads, suggesting a transfer

ment bond holdings, thereby weakening their balance sheets. This holds, of course, for Greek banks that have a large exposure to the Greek government, but also banks outside Greece hold significant quantities of Greek debt. Second, a fall in the market price of Greek sovereign bonds reduces the value of the collateral that banks can use to secure wholesale funding, and can trigger margin calls from counterparties. Third, deteriorating creditworthiness of Greece may reduce the value of government guarantees to Greek banks, be they explicit or perceived. Finally, sovereign downgrades often flow through to lower ratings for domestic banks because banks are more likely than other sectors to be affected by sovereign distress. The extent to which these channels affect bank stock prices depends on whether markets believe that other EU countries will support Greece. It was widely believed that other euro area countries would support Greece so as to avoid any contagion effects, despite the no-bailout clause of the Maastricht Treaty. If certain statements by leading European politicians cast doubt on such a bailout, however, bond prices of other sovereigns might be also affected. That is why we also examine whether Greek news affects bond prices of other highly indebted countries in the euro area. Increasing doubts about a general bailout would also make the last two of the above channels effective outside Greece. In our empirical analysis we therefore not only take banks' exposure to Greece into account, but also their exposure to other highly indebted euro area countries.

Using data for 48 European banks, our findings suggest that only news about the Greek bailout has a significant effect on bank stock prices, even on stock prices of banks without any exposure to Greece or other highly indebted euro area countries. News about the economic situation in Greece does not lead to abnormal returns. These results are similar to the ones by Aharony and Swary (1983) and provide some support for Cochrane's (2010) argument. However, we also find that the price of sovereign debt of Portugal, Ireland, and Spain responds to both news about Greece and news about a Greek bailout. Still, the finding that news about the economic situation in Greece affects sovereign bond yields of other highly indebted countries does not necessarily imply contagion as it is also in line with the so-called 'wake-up call' view.

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of default risk from the banking sector to the sovereign. However, thereafter both spreads increased together while the sovereign spread increase was larger for countries whose financial sectors were more distressed (see also Ejsing and Lemke 2011). In view of the large exposure of the banking sector to these sovereigns, the rise of sovereign CDS spreads has led to fears of a renewed banking crisis in the euro area.

According to this view a crisis initially restricted to one country may provide new information prompting investors to reassess the vulnerability of other countries, which spreads the crisis across borders (see, for instance Bekaert, Ehrmann, Fratzscher, and Mehl 2011).

The remainder of the chapter is structured as follows. Section 6.2 outlines our method, while Section 6.3 describes the data used. Section 6.4 presents the estimation results and robustness analyses. The final section concludes.

6.2 Method

We adopt an event study approach as is commonly used in finance (see MacKinlay 1997). In particular, we estimate a regression equation similar to the one used by Kho, Lee, and Stulz (2000) and Brewer III, Genay, Hunter, and Kaufman (2003), which for time t reads

$$R_{pt} = \alpha + \beta R_{mt} + \sum_{j=1}^{J} \gamma_j D_{jt}^{G} + \sum_{k=1}^{K} \delta_k D_{kt}^{B} + \epsilon_t, \tag{6.1}$$

where R_{pt} is the bank portfolio's daily excess return (i.e. the return minus the risk-free rate), R_{mt} is the excess return on the market portfolio, the event dummies D_t^G and D_t^B indicate trading days during which there was news about Greece and, respectively, news about the willingness of other countries to bailout Greece. As a result, the abnormal returns associated with these events are given by the γ_j and δ_k coefficients.

Our estimation window runs from the start to the end of 2010. A common difficulty in event studies is how to select the individual event dates in this window, and how to be certain that the news during these days was not anticipated and thus priced in by financial markets already during earlier days. We circumvent this problem by taking as our event dates the twenty trading days in 2010 during which the 10-year Greek government bonds experienced the largest price changes. These are the days during which markets priced in the largest news developments. We classify this news as news about Greece, to construct the D_{jt}^G dummy variable, or as news about the likelihood that Greece will be bailed out by other European countries, to construct the D_{jt}^B dummy variable. We obtain our news information from the Reuters U.K. archive of high-frequency news messages. Table 6.1 reports the selected event dates and the type of news that was most prominent during these days . The table shows that the changes in bond price fluctuations on the event days range from 2.6 to 32 percent in absolute value, which is large by conventional standards (the standard deviation of bond prices changes over the preceding year equals 0.6 percent). By using this approach to select our event dates, we avoid arbitrary judgement about which days to select as the date of an event, and also need not worry about whether news during these days was already priced in by the markets before.[3]

The aim of our analysis is to examine the overall impact of news about Greece and of news about Greece's bailout, and compare the impact of both types of news on bank stock prices. This way we can distinguish the impact of fiscal instability in Greece on bank market values from the impact of politicians' willingness to provide financial support to Greece. To facilitate doing so, we modify Equation (6.1) by omitting the twenty news dummies, and instead include one variable N_t^G for news about Greece, and one variable N_t^B for news about the bailout. We construct these variables such that $N_t^G = \sum_{j=1}^{J} D_{jt}^G R_{gt}$ and $N_t^B = \sum_{k=1}^{K} D_{kt}^B R_{gt}$, where R_{gt} denotes the change in the price of the 10-year Greek government bonds. As a result, the coefficient estimates for these variables, which we refer to as γ and δ respectively, can be interpreted as the abnormal return associated with a 1 percentage point change in the value of Greek government debt.

6.3 Data

We select the portfolio of banks using the stress tests performed by the Committee of European Bank Supervisors in July 2010. These stress test aimed at assessing the resilience of the EU banking system to possible adverse economic developments, and include a representative sample of 91 European banks which account for 65 percent of the European market in terms of total assets, see CEBS (2010). We use all banks

[3] We have to make a subjective judgement about attributing fluctuations in bond prices during those days to the two categories of news events that we distinguish. Fair (2002) shows that the news driving even extreme price fluctuations is not always easy to identify. However, in the current analysis this issue is somewhat mitigated by the fact that we only have to establish whether or not during an event day there was news about the bailout. If not, we automatically consider the news event as referring to the economic situation in Greece, without the need to precisely pin down the reason for the change in the Greek bond price. Still, we examine the robustness of our classification in the empirical section by identifying event dates using Greek sovereign CDS-spreads as well.

Table 6.1. Events inferred from changes in Greek government bond prices.

Event date	News description	Bailout	Return
27-01-2010	Greece on Wednesday denied press reports it had chosen Goldman Sachs to sell up to 25 billion euros of bonds to China, sending Greek government debt prices sharply lower and hitting the euro.	No	-3.50
28-01-2010	Germany and France denied a media report that they were planning to give financial aid to Greece, whose budget deficit hit an estimated 12.7 percent in 2009. Athens says it is seeking funds only through the markets, mainly in Europe.	Yes	-3.10
10-02-2010	European shares rose on Wednesday on hopes of a possible European Union rescue plan for Greece.	Yes	2.63
06-04-2010	Markets pushed Greece's risk premium to a euro lifetime high amid growing doubts over the country's capacity to resolve its debt crisis and fresh scepticism about a European Union-International Monetary Fund aid mechanism.	No	-3.17
12-04-2010	The euro zone agreed on a 30-billion-euro package of three-year loans at interest of about 5 percent if Greece seeks help. The International Monetary Fund would also be expected to supply 15 billion euros in the first year.	Yes	3.35
23-04-2010	Greek bank shares erased gains posted earlier in the day on concerns over possible delays in the activation of an EU/IMF aid package.	Yes	-3.04
26-04-2010	Germany said on Monday it could offer aid for Greece within days if it agreed to painful new austerity measures, but rescue jitters pushed the cost of insuring against a Greek debt default to a record high.	Yes	-5.50
03-05-2010	Markets reacted to a record 110 billion euro bailout for Greece, although investors doubted it would offer more than temporary relief to a euro zone shaken by divisions and saddled with high debt.	Yes	4.17
04-05-2010	Doubts whether debt-stricken Greece has the resolve to make sharp spending cuts fuelled safe-haven demand for bonds.	No	-6.26
05-05-2010	Fear that a euro-zone debt crisis may spread beyond Greece knocked the euro below the $1.29 level for the first time in more than a year on Wednesday and rattled bond markets in Portugal and Spain as anxious investors snapped up U.S. dollars.	No	-5.74
06-05-2010	Investors rushed to the perceived safety of the U.S. dollar and Japanese yen as the European Central Bank offered no new measures to ease a Greek debt crisis after a meeting earlier the day.	Yes	-2.86
07-05-2010	Greece's drastic belt-tightening to secure emergency aid risks plunging the economy into a deeper recession, threatening delivery of key fiscal targets and prolonging the debt crisis.	No	-10.59
10-05-2010	Investor sentiment receives a boost from news of an European Union plan to halt the spread of Greece's fiscal woes.	Yes	31.97
14-05-2010	European bank shares fell over 3 percent on Friday as renewed concerns about losses from exposures to Greece unsettled investors.	No	-4.08
18-05-2010	Greece received a 14.5 billion euro loan from the European Union and can now repay its immediate debt, a development that helped to steady global investor's jitters.	Yes	4.01
15-06-2010	A recovery in stocks and the euro fizzled out after Moody's downgraded Greece to junk status.	No	-5.82
23-06-2010	Communist trade unionists blocked travellers from boarding ships at Greece's largest port on Wednesday, stranding tourist ferries as part of protests against austerity measures in the debt-choked nation.	No	-3.42
11-10-2010	The International Monetary Fund said on Sunday that bailout loans to Greece could be stretched out or replaced if refinancing worries lingered in markets, but it currently has no concrete plans to do so.	Yes	3.47
27-10-2010	Greece's 2009 budget deficit, whose wildly gyrating figures triggered the country's fiscal crisis, will be set "once and for all" at above 15 percent of GDP, the finance minister said.	No	-4.51
04-11-2010	Greece resumes air freight after parcel bomb spate. Greek authorities have blamed leftist militants for the bombs, which may be intended to spur an anti-government vote in Sunday's local elections in protest against austerity plans.	No	-2.66

included in the stress test for which Thomson Datastream reports a stock price quote during at least 90 percent of the 261 trading days in 2010, which results in a sample of 48 banks. These banks and their exposures to Greece and three other highly indebted countries, i.e. Ireland, Portugal, and Spain (GIPS-countries), are listed in Table 6.2. The table shows that there is quite some heterogeneity in the sample with respect to the exposures of individual banks, which range from 0 to 417 percent of their core tier 1 capital buffers.

For the banks in the table we obtain from Thomson Datastream daily time series for 2010 with market capitalisation expressed in local currencies (see Chapter 3). To construct the returns on the bank portfolios that are included as the dependent variable in Equation (6.1), we use these time series to construct five portfolios with logarithmic changes in market capitalisation averaged over: (i) all banks, (ii) all banks with an exposure to Greece, (iii) all banks without an exposure to Greece, (iv) all banks with an exposure to at least one of the four GIPS-countries, and (v) all banks without an exposure to any of the GIPS-countries.[4] In addition to focusing on the impact of Greek news on bank portfolios, we analyse the impact of news on bond prices of Ireland, Portugal, and Spain. To this end, we use as the dependent variable Thomson Datastream price changes of these countries' 10-year government bonds.

When analysing abnormal returns on the portfolios of bank equity we use the return on the FTSEurofirst 300 index as the market index. When analysing the impact on sovereign bond prices we use as the market index the J.P. Morgan Index of European Government Bonds with yields to maturity between 7 and 10 years. We express the returns on bank portfolios, government bonds, and stock and bond price indices in excess of the risk-free rate, for which we take the one-day EONIA interest rate.

[4] By focusing on the impact of news on the price of bank stocks rather than on the price of bank bonds, we aim to avoid that our results are affected by government guarantees for banks that are considered to be 'systemically important'. While these guarantees would reduce the response of bank bond prices to any contagion effects, they are not designed to protect shareholders whose capital is designed to bear losses. See also King (2009).

Table 6.2. Banks included in the sample.

Bank name	Country	Exposure in % of core tier 1 capital to Greece	to GIPS
Austria	Erste Group Bank	6.58	11.88
	Raiffeisen Zentralbank Oesterreich	0.22	0.31
Belgium	Dexia	21.33	48.57
	KBC Bank	6.76	24.01
Cyprus	Bank of Cyprus	74.77	88.83
	Marfin Popular Bank	122.07	126.34
Denmark	Danske Bank	0.00	4.45
	Jyske Bank	5.06	6.44
	Sydbank	0.00	0.00
Finland	Op-Pohjola	0.40	1.19
France	BNP Paribas	7.96	17.66
	Credit Agricole	1.63	10.58
	Société Générale	12.18	17.28
Germany	Commerzbank	9.82	25.74
	Deutsche Bank	4.89	12.80
	Deutsche Postbank	27.25	58.56
Greece	Alpha Bank	85.64	85.64
	EFG Eurobank Ergasias	139.43	139.43
	National Bank of Greece	260.29	260.29
	TT Hellenic Postbank	417.18	417.18
Hungary	FTB Mortgage Bank	0.00	0.00
	OTP Bank	0.00	0.00
Ireland	Allied Irish Banks	0.48	56.49
	Bank of Ireland	0.00	12.39
Italy	Banco Popolare	1.25	3.37
	Intesa Sanpaolo	2.74	5.18
	Monte dei Paschi di Siena	0.38	2.72
	UBI Banca	0.37	0.37
	Unicredit	2.05	4.17
Netherlands	ING Bank	7.13	16.25
	SNS Bank	3.54	17.25
Poland	PKO Bank Polski	0.00	0.00
Portugal	Banco BPI	22.67	232.22
	Banco Comercial Portugues	11.77	30.66
Spain	Banco de Sabadell	0.00	95.45
	Banco Pastor	2.03	144.28
	Banco Popular Español	0.00	97.33
	Bankinter	0.00	75.73
	Grupo BBVA	1.08	194.78
	Grupo Santander	0.54	95.84
Sweden	Nordea	1.27	1.46
	Swedbank	0.00	0.00
	Svenska Handelsbanken	0.00	0.00
	Skandinaviska Enskilda Banken	1.51	3.02
United Kingdom	Barclays	0.78	11.99
	HSBC	1.58	2.91
	Lloyds Bancking Group	0.00	0.30
	Royal Bank of Scotland	3.20	12.35

6.4 Results

6.4.1 Main results

The fear for contagion by policy makers is easy to understand once taking a quick look at the raw data. Of the twenty days with extreme returns on Greek sovereign bonds, the average bank experienced a return equal to 3.26 percent when the news was positive, and -1.62 percent when the news was negative. Hence, it is easy to conclude from these casual observations that bank stock prices are strongly driven by the risk that Greece might go bankrupt.

Table 6.3 reports the abnormal returns for news about Greece and news about the bailout of Greece. They are obtained as the coefficient estimates from regressing the time series of daily portfolio returns during 2010 on the news variables (as well as on a constant and the market index). Two observations stand out from the first row in the table. First, news about the economic situation of Greece does not have a significant impact on the market value of the equity portfolio including all banks in the sample. Second, news about the bailout of Greece does significantly affect the market value of this portfolio. A one percent change in the Greek government bond price induced by news about a bailout leads to a 0.12 percent change in banks' market value.

The first finding implies that expectations by financial markets regarding losses for banks do not change when the probability of a Greek default changes due to news about Greece's economic situation. This includes losses expected from direct exposures to Greece, but also losses expected from indirect exposures via other banks. This result suggests that market participants do not expect bank losses associated with an actual Greek default to be large in magnitude.

The second finding implies that the prospect of a bailout has a stabilising impact on bank stock prices. When Greek bonds rise in value due to positive news about a bailout, bank stock prices rise as well (and vice versa). Apparently, financial markets attach a substantial value to the willingness of governments to shield banks from losses on their sovereign exposures by bailing out failing euro countries.

To examine the impact of news about Greece and news about a Greek bailout in more detail, the next two rows in the table distinguish banks with an exposure to

Table 6.3. Impact of bond-based news about Greece and about the bailout of Greece on bank equity and sovereign bonds

Regression equation: $R_{pt} = \alpha + \beta R_{mt} + \gamma N_{gt}^{G} + \delta N_{gt}^{B} + \epsilon_t$

	News about Greece		News about the bailout	
	γ	$t-$stat.	δ	$t-$stat.
Abnormal return on bank equity				
All banks	0.016	0.23	0.124	9.45
Banks exposed to Greece	0.017	0.23	0.132	9.41
Banks not exposed to Greece	0.012	0.18	0.101	4.62
Banks exposed to GIPS	0.016	0.21	0.132	9.15
Banks not exposed to GIPS	0.015	0.25	0.072	3.63
Abnormal return on sovereign bonds				
Portugal	0.214	3.51	0.282	30.40
Ireland	0.160	2.79	0.234	20.61
Spain	0.052	1.96	0.113	24.64

Reported $t-$statistics are calculated from Newey-West standard errors.

Greece from banks without an exposure to Greece. The results do not differ qualitatively from those for the average sample of banks, as news about the economic situation of Greece never leads to significant abnormal returns, while news about the bailout of Greece always leads to such abnormal returns. As the table shows, even banks without an exposure to Greece respond to news about Greece's bailout. The next two rows consider banks with or without an exposure to any of the GIPS-countries. The results confirm the previous results: banks with an exposure to any of the GIPS-countries do not respond to news about Greece, while even banks without such an exposure respond to news about the bailout. Our finding that news about Greece does not have an impact on bank stock prices while news about a bailout does, suggests that markets consider news about the bailout to be a signal of European governments' willingness in general to use public funds to protect private investors against losses. When governments indicate, for instance, that they will not rescue Greece, markets consider this to be a disturbing signal mainly because it might imply governments also will not engage in any other financial sector rescue operations anymore.

The last three rows of the table examine to what extent the prices of sovereign debt of the other three GIPS-countries, Ireland, Portugal, and Spain, respond to news about the economic situation in Greece and news about a Greek bailout. In this case we do find significant abnormal returns associated with news about the economic situation in Greece, while as before news about the bailout leads to abnormal returns as well. The $t-$statistics for news about the bailout are a factor ten larger than those for news about Greece itself, although results from a Wald-test show the absolute returns of both types of news are not statistically different from each other.

That news about the bailout leads to abnormal returns in other countries as well is not surprising, as the willingness of euro countries to bailout Greece obviously says a lot about their willingness to bailout other GIPS-countries as well. However, that news about the economic situation in Greece leads to abnormal returns on other countries' bond prices might be more surprising, as it does not lead to abnormal returns on bank stock prices (including the sub-sample with an exposure to the GIPS). An explanation for the impact of news about Greece on other countries is that there is a learning effect. Others refer to this as a 'wake-up call': a crisis initially restricted to one country may provide new information prompting investors to reassess the vulnerability of other countries, which spreads the crisis across borders (Goldstein, Kaminsky and Reinhart, 2000). According to this view, domestic fundamentals are likely to play a dominant role in the transmission of the crisis (Bekaert, Ehrmann, Fratzscher and Mehl, 2011). The ability of Greece to reduce its budget deficit and government debt, and the response of rating agencies to these attempts, are quite informative about the likelihood that other indebted countries will be able to quickly reduce their debt levels as well. If Greece does not succeed to credibly commit to a sustainable fiscal policy, the probability that other GIPS-countries will manage to do so may be small as well. Our results suggest that the abnormal returns in GIPS-countries after news about Greece's economic situation are especially due to such learning effects.

6.4.2 Robustness analyses

As a robustness analysis, we use changes in Greek 10-year senior sovereign CDS-spreads to identify event dates, instead of changes in Greek sovereign bond prices. This way we examine the robustness of our results to using a different measure of sovereign default risk. In addition, as the days with extreme returns in CDS-spreads

Table 6.4. Impact of CDS-based news about Greece and about the bailout of Greece on bank equity and sovereign CDS-spreads

Regression equation: $R_{pt} = \alpha + \beta R_{mt} + \gamma N_{gt}^{G} + \delta N_{gt}^{B} + \epsilon_t$

	News about Greece		News about the bailout	
	γ	$t-$stat.	δ	$t-$stat.
Abnormal return on bank equity				
All banks	-0.203	-0.92	-1.165	-7.00
Banks exposed to Greece	-0.217	-0.89	-1.197	-7.26
Banks not exposed to Greece	-0.160	-0.47	-1.068	-5.14
Banks exposed to GIPS	-0.229	-1.01	-1.209	-6.74
Banks not exposed to GIPS	-0.021	-0.06	-0.854	-6.14
Abnormal return on sovereign bonds				
Portugal	0.180	2.97	0.367	4.72
Ireland	0.070	1.62	0.129	3.39
Spain	0.088	3.02	0.130	4.18

Reported $t-$statistics are calculated from Newey-West standard errors.

differ in several cases from the days with extreme returns in sovereign bond prices, while sometimes there seems to be no clear news driving the event, we this way examine the robustness of our results to the identification and classification of the news events. All CDS-spreads are obtained from Thomson Datastream. Table 6.4 shows the outcomes. The results are similar to the ones presented above, as for banks news about Greece does not lead to abnormal returns while news about the bailout does.[5] Interestingly, for all bank portfolios the coefficients for news about Greece and news about a bailout are now significantly different from each other. Abnormal returns in countries' CDS-spreads, which we use as the dependent variable instead of changes in bond prices, are significant as well for both types of news (although for Ireland only at the ten percent level). These results confirm those from our main analysis.

We also perform a robustness analysis where we include additional news variables for events where the news is negative, i.e. for those days where the Greek bond price declines. This way we examine whether investors respond asymmetrically to news events. Neither for bank portfolios nor for government bonds is there evidence for

[5] The signs of the values in the table are opposite to the signs in Table 6.3, since when default risk increases CDS-spreads rise while bond prices decline.

such an asymmetric response.

Finally, we do a robustness analysis where we construct a weighted average portfolio of bank equity returns, using as weights the exposure to Greece as a percentage of their core tier 1 equity buffers. As these exposures are likely to change over time instead of being equal to the values in Table 6.2 throughout the entire sample period, we do this exercise for robustness only. The results show that both types of news have a significant impact on the weighted portfolio, although for news about Greece only at the ten percent level. However, once we remove the four banks for which the exposure was larger than 100 percent of their equity, of which three are Greek and one is from Cyprus, only news about the bailout has a significant impact. When we construct weighted portfolios with weights equal to the combined exposure to the GIPS as a percentage of core tier 1 equity, the results confirm the finding from our main analysis that only news about the bailout has a significant impact.

6.5 Conclusion

Using an event study approach, we examine the impact of news about Greece and news about a Greek bailout on bank stock prices in 2010 using data for 48 European banks. We first identify the twenty days with extreme returns on Greek sovereign bonds and categorise the news events during those days into news about Greece and news about the prospects of a Greek bailout. Our findings suggest that only news about a bailout has a significant effect on bank stock prices, even on stock prices of banks without any exposure to Greece or other highly indebted euro area countries. News about the economic situation in Greece does not lead to abnormal returns. This combination of results suggest that financial markets consider news about the bailout to be a signal of European governments' willingness in general to use public funds to combat the financial crisis. In contrast, the price of sovereign debt of Portugal, Ireland, and Spain, responds to both news about the economic situation of Greece and news about a Greek bailout. A plausible explanation for the impact of news about Greece on the bond prices of other countries is that there is a 'wake-up call': a crisis initially restricted to one country may provide new information prompting investors to reassess the vulnerability of other countries, which spreads the crisis across borders.

Chapter 7

Conclusion and Policy Implications

This thesis focused on the question to what extent simultaneous instability across financial markets or institutions is due to contagion, and to what extent it is due to adverse common shocks. The difference between both concepts is important from an academic as well as a policy perspective. While in case of contagion, instability of one market or institution *causes* the instability of another, in case of a common shock, markets or institutions simultaneously become unstable due to a third factor such as an increase in global investor risk aversion. Both effects are difficult to disentangle empirically, the key issue being that controlling for common shocks is not straightforward as they often cannot directly be observed. Nonetheless, policy makers and the public at large generally consider financial contagion to be the obvious culprit once financial markets or institutions become unstable simultaneously.

Chapter 2 focused on the banking sector to point out that this explanation is less obvious than it might seem at first sight, and developed a theoretical model to show how common shocks can be an important reason for banks becoming unstable simultaneously. The model shows that the supply of illiquidity insurance through the Lender of Last Resort stimulates banks to take risks in such a manner that their balance sheets become highly similar. First, the Lender of Last Resort causes bank funding structures to become more homogeneous, with all banks increasing their leverage and their use of relatively short-term funds. Second, the Lender of Last Resort causes bank asset portfolios to become highly correlated amongst each other, as the prospect of receiving liquidity support stimulates banks to diversify rather than specialise in activities. Through both effects, the provision of illiquidity insurance causes banks' balance sheets to become increasingly similar and, consequently, more exposed to adverse common shocks. This exposure provides an explanation additional to the contagion hypothesis for the simultaneous occurrence of bank failures. The model shows that regulatory capital requirements can actually stimulate diversification, increasing banks' exposure to common shocks, while regulatory liquidity requirements reduce all forms of bank risk-taking examined.

Chapter 3 provided an overview of common definitions of contagion in the empirical literature, and then showed that part of the literature on stock market contagion is biased towards finding evidence for contagion, as it focuses on stock market returns expressed in US dollars instead of in local currencies. By doing so, fluctuations in the

US dollar exchange rate effectively act as a common driving force behind the returns on the examined markets, creating the impression of contagion between them where in reality there is none.

Chapter 4 examined the common practice to empirically analyse contagion between stock markets by reporting results for co-movement with a predefined ‘source’ market and during a predefined ‘crisis’ period or quantile (i.e. a set of extreme returns exceeding a given threshold). The analysis showed that many arbitrary combinations of markets with time periods or return quantiles exist for which co-movement is significantly elevated. As these sub-samples cannot be related to particular crises events or extreme return thresholds, any increases in synchronicity during crisis times cannot necessarily be interpreted as evidence for contagion

Chapter 5 zoomed in on the banking sector, a part of the financial system that is believed to be especially vulnerable to contagion effects. The chapter examined whether financial markets expected bank defaults to be contagious during the 2007 Global Financial Crisis. The strategy to identify contagion was based on the presumption that if financial markets expect one bank’s default to cause other banks to suffer losses too, as implied by the contagion hypothesis, an increase in this bank’s default probability should lead to a decline in the other banks’ market valuation. For a global sample of the one hundred largest banks, we tested for contagion by estimating a panel regression model, explaining changes in banks’ market values from an estimated market factor and from changes in other banks’ CDS-spreads or default probabilities. The results indicated that changes in bank market values are correlated due to the common market factor, but also show that a change in one bank’s CDS-spread or default probability hardly affects the market’s valuation of other banks in the sample. This finding indicates that the observed declines in banks’ market value during the crisis can hardly be explained by contagion effects, but are predominantly due to adverse common shocks affecting the banking sector as a whole.

That contagion risks are small compared to the impact of common shocks was also the main finding of Chapter 6. This chapter used an event study approach to examine the impact of news about Greece and news about a Greek bailout on bank stock prices in 2010 using data for 48 European banks. Only news about the Greek bailout turned out to have a significant effect on bank stock prices, even on stock prices of banks without any exposure to Greece or other highly indebted euro area countries. News about the economic situation in Greece did not lead to excess returns in bank stock prices. This result suggests that news about the bailout acts as a common shock affecting banks' market values, with markets interpreting this news as a signal of European governments' willingness in general to use public funds to combat the financial crisis. Consistent with this interpretation, the price of sovereign debt of Portugal, Ireland, and Spain responds to news about the Greek bailout as well. However, these bond prices are also found to respond to news about the economic situation of Greece. A plausible explanation for this impact of news about Greece on the bond prices of other highly indebted countries is that there is a 'wake-up call': a crisis initially restricted to one country may provide new information prompting investors to reassess the vulnerability of other countries, which spreads the crisis across borders. Such learning effects are not to be confused with the impact of financial contagion.

All in all, the results from the previous chapters suggest that the role of contagion in explaining simultaneous instability across financial markets and institutions is relatively small compared to the impact of common shocks. Naturally, there are caveats to this result. An important one is that markets might not price contagion risk, either because they are inefficient or because investors believe with certainty that the consequences of any contagion will be fully mitigated by financial supervisors and government rescue operations. This explanation still implies, however, that the observed market turmoil cannot be due to investors fearing for contagion. An alternative explanation, of course, is that the analyses adopted are inadequate for reasons unknown at the time of writing. Nonetheless, their outcomes highlight that any knee-jerk referencing to contagion effects is a questionable response when financial markets or institutions become unstable simultaneously. An interesting exercise is therefore to take the above findings at face value, and evaluate their implications for economic policy. In particular, if common adverse shocks rather than financial contagion are the main cause of simultaneous instability across financial markets and institutions, this has at least three policy implications.

First, policy makers should have more attention for the risks stemming from similarities across banks' balance sheets, since this type of sector homogeneity is an important reason that large parts of the financial sector can simultaneously become unstable. From a social welfare perspective, it could be optimal when banks avoid exposing themselves to the same type of adverse shocks, and specialise in activities rather than diversifying across them. Reducing balance sheet similarities this way might prove more effective to foster financial stability than trying to identify 'systemically important' banks, even though the latter attempts have until now received most attention from policy makers. The analysis in Chapter 2 showed that limiting bank maturity transformation though imposing liquidity requirements could be an effective means to reduce similarities between banks, and thereby reduce their exposure to common shocks.

Second, the opacity of banks' and other financial intermediaries' balance sheets might have caused investors to erroneously interpret some adverse shocks to one or a few banks as a common shock to the banking sector as a whole. Under asymmetric information, investors will evaluate the value or riskiness of their own bank's assets using public signals about the asset quality of other banks. A bad signals can then lead to a classic lemons' market effect as described by Akerlof (1970), which is likely to have played an important role in the drying up of the market for complex mortgage-backed securities. To reduce its vulnerability to such effects, each bank should provide transparency about the composition of its balance sheet. This increases investor knowledge about the quality of bank assets, so that banks become less dependent on investor 'confidence' therein. Imposing objective accounting rules based on market valuation and requiring full consolidation and disclosure of risks on banks' balance sheets would be a natural first step.

Third, the use of generally costly bank rescue operations to safeguard financial stability comes under question, since rescuing one troubled bank not so much prevents contagion to other banks, but merely assures these other banks' financiers that once needed they will receive a bailout as well. While during a crisis such rescue operations could have a stabilising effect, they can become a source of instability when doubts arise about governments' ability to live up to their (implicit) promises. In addition, if banks anticipate any rescue operations by increasing their risk-taking in good times, the *ex ante* contribution of such bailouts to financial stability becomes rather limited. The actual bailout then becomes nothing more than the transfer of a subsidy that was already factored into banks' business models and risk management policies. Such implicit guarantees reduce market participants' regard for economic fundamentals, and sow the seeds of a future financial crisis.

The findings in this thesis also have some implications for future research. The theoretical model in the first part related bank risk-taking to the term structure of interest rates, with a larger spread between long-term and short-term interest rates stimulating banks to take more risk. As a steeper term structure is generally associated with an upswing in the business cycle, the model suggests a source of pro-cyclicality in bank risk-taking that is unexplored in the literature. It also suggests additional research into monetary policy, which through its impact on the term spread could affect bank risk-taking as well. The second, empirical part of this thesis calls for new research into the nature of similarities across financial markets and institutions, so as to gain more insight into their vulnerability to adverse common shocks. The literature's focus on financial contagion as the main source of financial system instability has left this area largely unexplored. Filling in this gap is however outside the scope of the present thesis, which merely provides some evidence that contagion is not as omnipresent as is generally believed. By showing that this finding has implications for economic policies to prevent and manage financial crises, it aims to trigger the reader in thinking carefully about the question of whether financial system instability is due to contagion, or to common shocks? Doing so would be valuable for both academics and policy makers alike.

Chapter 8

Samenvatting (Summary in Dutch)

Sinds 2007 hebben zich op de financiële markten ontwikkelingen voorgedaan die tot dat moment voor vrijwel onmogelijk werden gehouden. Wat oorspronkelijk beperkt leek tot de wanbetaling op een aantal slechte Amerikaanse hypotheekleningen, ging over in de grootste financiële crisis sinds de depressie van de jaren dertig uit de vorige eeuw. Tijdens deze crisis crashten aandelenbeurzen, stegen risicopremies tot grote hoogten, droogden geldmarkten op, gingen financiële instellingen bankroet, en balanceerden zelfs nationale overheden op de rand van een faillissement. Terwijl zulke gebeurtenissen op zichzelf zelden voorkomen, hebben zij inmiddels geleid tot wat bekend staat als de Mondiale Financiële Crisis van 2007 en daarna. Deze plotselinge samenkomst van risico's maakt dat de mogelijkheden tot risicospreiding afnemen wanneer zij juist het hardst nodig zijn, en vormt een substantiële bedreiging vormt voor de stabiliteit van het financieel stelsel.

Het zich gelijktijdig materialiseren van risico's heeft bij investeerders en beleidsmakers de angst aangewakkerd dat instabiliteit overslaat tussen financiële markten en instellingen, waarbij instabiliteit van één markt ertoe leidt dat ook andere markten worden gedestabiliseerd. Verwijzend naar een term uit de medische wetenschap wordt dit fenomeen ook wel aangeduid als besmetting. Hoewel de economische literatuur dit begrip nog niet eenduidig heeft weten te definiëren, beschouwen beleidsmakers en het grote publiek financiële besmetting als de voor de hand liggende boosdoener wanneer verschillende delen van het financieel stelsel gelijktijdig instabiel worden.

Hoewel zij vaak met elkaar worden geassocieerd, is gelijktijdige instabiliteit van financiële markten of instellingen niet per definitie het gevolg van besmetting. Immers, behalve dat instabiliteit van de ene markt of instelling de *oorzaak* kan zijn van instabiliteit van de andere, kunnen beide markten of instellingen ook gelijktijdig instabiel zijn geworden door een negatieve gemeenschappelijke schok. Een simpel voorbeeld van zo'n gemeenschappelijke schok is een wereldwijde toename van risico-aversie onder investeerders, wat er bijvoorbeeld toe leidt dat internationale aandelenmarkten dalen ook zonder dat er een directe economische relatie tussen hen bestaat. Correlatie van instabiliteit tussen financiële markten en instellingen impliceert dus niet automatisch dat er sprake is van besmetting. In de context van een financiële crisis kan een parallel worden getrokken met een domino-effect: de dominostenen kunnen omvallen doordat de één de ander aanstoot (besmetting), of doordat een windvlaag ze allen omblaast zonder dat er interactie tussen hen is (gemeenschappelijke schok). Beide effecten hebben zeer verschillende implicaties voor beleidsmakers die het financiële systeem willen stabiliseren. Als het grootste risico voortkomt uit besmetting dan is het stabiliseren van één dominosteen voldoende om ook alle andere overeind te houden, terwijl in het geval van een gemeenschappelijke schok de dominostenen alleen kunnen worden gestabiliseerd door het openstaande raam te sluiten.

Het kernprobleem bij het in de praktijk onderscheiden van besmetting en gemeenschappelijke schokken als oorzaken van financiële instabiliteit, is dat veel gemeenschappelijke schokken niet direct meetbaar zijn. Empirisch onderzoek naar het meten van financiële besmetting begint daarom doorgaans met het formuleren van enkele veronderstellingen over het tijdsverloop van deze schokken, en beschouwt vervolgens de correlatie tussen financiële markten die niet met deze aannames kan worden verklaard als het resultaat van besmettingseffecten. Omdat verschillende economen uiteenlopende veronderstellingen hanteren, is de vraag of tijdens financiële crises besmetting tussen markten optreedt nog steeds onderwerp van discussie in de literatuur.

Om dezelfde reden als hierboven is ook besmetting tussen financiële instellingen onderwerp van discussie, waarbij de aandacht met name uitgaat naar de bankensector. Opvallend in dit verband is een speech uit 2010 van Thomas Huertas, destijds vicevoorzitter van het Europese Comité van Bankentoezichthouders. Huertas betoogt dat de bijna volledige instorting van het financieel stelsel na het faillissement van Lehman Brothers op 15 September 2008 niet zozeer te wijten was aan besmettingseffecten veroorzaakt door het faillissement, maar aan de gemeenschappelijke schok die uitging van de plotselinge twijfel van investeerders aan de bereidheid en capaciteit van de Amerikaanse overheid om omvallende banken met staatsteun te hulp te komen.

Dit proefschrift analyseert in welke mate gelijktijdige instabiliteit van financiële markten en instellingen te wijten is aan financiële besmetting, en in welke mate deze een gevolg is van negatieve gemeenschappelijke schokken. Dit thema vormt de rode draad door de hoofdstukken. Hoofdstuk 2 kiest hierbij een theoretisch perspectief, terwijl de hoofdstukken daarna een empirische benadering hanteren.

Hoofdstuk 2 laat binnen een theoretisch model zien dat gemeenschappelijke schokken een belangrijke verklaring kunnen zijn voor het feit dat banken vaak gelijktijdig instabiel worden. Het model zet uiteen hoe het verstrekken van liquiditeitsteun door de monetaire autoriteiten een stimulans aan banken geeft om dezelfde soort risico's te nemen, met als gevolg dat hun balansen sterk op elkaar gaan lijken. Banken anticiperen op liquiditeitsteun door dezelfde financieringstructuur te kiezen: weinig eigen vermogen en veel kortlopende schuld. Daarnaast leidt de verwachting van liquiditeitsteun ertoe dat banken hun activa diversifiëren in plaats van zich in enkele activiteiten te specialiseren, waardoor winsten en verliezen meer samenvallen tussen banken. Beide effecten zorgen ervoor dat de bankensector homogener wordt en kwetsbaar is voor gemeenschappelijke schokken.

Hoofdstuk 3 geeft een overzicht van de verschillende definities van besmetting die in de empirische literatuur worden gehanteerd. Vervolgens laat het hoofdstuk zien dat de literatuur over besmetting tussen internationale aandelenmarkten de omvang van besmettingseffecten vaak overschat, door zich te richten op koersmutaties omgerekend naar Amerikaanse dollars. Wanneer de koersmutaties in twee te vergelijken markten naar dollars worden omgerekend in plaats van in de lokale munteenheid te worden uitgedrukt, worden de in beide markten gemeten koersmutaties immers op dezelfde manier vertekend door fluctuaties in de dollarkoers. Een stijging van de dollarkoers leidt dan op beide markten tot een daling van de in dollars uitgedrukte aandelenkoersen, en creeërt daarmee de schijn van besmetting tussen deze markten zonder dat hier daadwerkelijk sprake van is. Deze vertekening kan worden vermeden door zich te richten op koersmutaties uitgedrukt in de lokale munteenheid.

Hoofdstuk 4 analyseert besmetting tussen aandelenmarkten. Deze vorm van besmetting wordt vaak onderzocht door een markt te kiezen die als 'bron' kan gelden van mogelijke besmettingseffecten tijdens een periode die als 'crisis' wordt aangemerkt. De keuze voor de 'bron' en de 'crisis' is doorgaans op veronderstellingen gebaseerd. Besmetting wordt vervolgens gedefinieerd als het bovengemiddeld sterk samenvallen van koersmutaties in andere markten met mutaties in de bronmarkt tijdens de crisisperiode. Hoofdstuk 4 laat echter zien dat ook regelmatig van zulke samenvallende koersmutaties sprake is wanneer de 'bron' en de 'crisis' volstrekt willekeurig worden gekozen. Dit resultaat suggereert dat het bovengemiddeld sterk samenvallen van koersfluctuaties tussen markten op zichzelf niet voldoende is om van besmetting te kunnen spreken.

Hoofdstuk 5 richt zich op het meten van besmetting in de bankensector, en onderzoekt in welke mate financiële marktpartijen verwachtten dat bankfaillissementen tijdens de Mondiale Financiële Crisis besmettelijk zouden zijn. De methode is gebaseerd op het uitgangspunt dat wanneer markten verwachten dat een faillissement van de ene bank zal leiden tot besmetting van de andere, een toename in de faillissementskans van de ene zal leiden tot een afname van de beurswaarde van de andere. Wij toetsen of sprake is van dit effect in een steekproef van de honderd grootste Amerikaanse en Europese banken tijdens de periode 2007–2009. De analyse laat zien dat de marktwaardes van banken onderling sterk gecorreleerd zijn, maar dat deze marktwaardes amper worden beïnvloed door veranderingen in de faillissementskans van andere banken. Dit resultaat suggereert dat besmettingseffecten maar een zeer geringe rol hebben gespeeld bij de dalende marktwaardes van banken tijdens de Mondiale Financiële Crisis.

Hoofdstuk 6 onderzoekt de Griekse schuldencrisis, in het bijzonder of voor het jaar 2010 nieuws over Griekenland en nieuws over een mogelijke redding van Griekenland invloed hebben op de marktwaardes van Europese banken en staatsobligaties. Het blijkt dat alleen nieuws over een Griekse redding de marktwaarde van banken beïnvloedt, zelfs wanneer deze banken niet hebben belegd in staatsobligaties van Griekenland of andere Eurolanden met hoge schuldniveaus (Ierland, Portugal en Spanje). Dit resultaat illustreert dat nieuws over reddingsoperaties het effect heeft van een gemeenschappelijke schok, waarbij marktpartijen na nieuws over een eventuele redding van Griekenland hun verwachtingen bijstellen over de bereidheid van Europese overheden in het algemeen om met publiek geld de crisis te bestrijden. Deze interpretatie wordt ondersteund door de bevinding dat nieuws over een reddingsoperatie van Griekenland ook invloed heeft op de marktwaarde van de andere Europese staatsobligaties die zijn onderzocht.

De analyses in dit proefschrift suggereren dat de rol van besmetting als oorzaak van gelijktijdige instabiliteit van financiële markten en instellingen beperkt is in verhouding tot de impact van negatieve gemeenschappelijke schokken. Hoewel bij deze analyses ook nuanceringen kunnen worden gemaakt, plaatsen zij vraagtekens bij de vaak reflexmatige verwijzingen naar besmetting als verklaring voor gelijktijdige uitbraken van financiële instabiliteit. De bevindingen hebben bovendien ten minste drie beleidsimplicaties.

Beleidsmakers moeten meer aandacht hebben voor de homogeniteit van de bankensector. De overeenkomsten tussen bankbalansen maken deze sector gevoelig voor gemeenschappelijke schokken. Vanuit maatschappelijk perspectief kan het daarom wenselijk zijn dat banken zich specialiseren in activiteiten in plaats van tussen verschillende activiteiten te diversifiën. Door op deze manier overeenkomsten tussen bankbalansen te verkleinen wordt de financiële stabiliteit vermoedelijk meer bevorderd dan door het voorkomen van besmettingseffecten na het faillissement van een 'systeemrelevante' financiële instelling. De analyse in Hoofdstuk 2 laat zien dat het opleggen van strenge liquiditeitseisen die looptijdtransformatie terugdringen de homogeniteit van de bankensector effectief beperkt.

Ten tweede moet de ondoorzichtigheid van bankbalansen worden teruggedrongen. Dit voorkomt dat investeerders negatieve schokken die slechts een beperkt aantal banken treffen ten onrechte interpreteren als schokken die gemeenschappelijk zijn voor de sector als geheel. Wanneer balansen van banken ondoorzichtig zijn gebruiken investeerders nieuw beschikbare informatie over de gezondheid van de ene bank immers ook om hun oordeel over de gezondheid van andere banken bij te stellen. Dit effect kan een belangrijke rol hebben gespeeld in het opdrogen van de markt voor complexe hypotheekobligaties. Om de kwetsbaarheid van banken voor dit soort *lemons' market* effecten te verminderen, moeten banken meer informatie verstrekken over hun balanssamenstelling en hun activa zoveel mogelijk waarderen op de actuele marktwaarde. Dit vergroot het inzicht van investeerders in het bancaire risicobeheer, zodat banken minder afhankelijk worden van hun 'vertrouwen' daarin.

Ten derde kunnen vraagtekens worden geplaatst bij pogingen van overheden om met kostbare steunoperaties aan individuele banken de financiële stabiliteit te waarborgen. Wanneer gemeenschappelijke schokken de belangrijkste bron zijn van instabiliteit, werkt het redden van de ene bank immers hooguit stabiliserend voor andere banken door te suggereren dat deze andere banken indien nodig ook op staatsteun kunnen rekenen. Op het hoogtepunt van een crisis hebben zulke reddingsoperaties weliswaar een stabiliserend effect, maar zij kunnen ook een bron van instabiliteit worden wanneer twijfels in de markt ontstaan over het vermogen van overheden om hun (impliciete) garanties gestand te doen. Wanneer banken bovendien in goede tijden op reddingsoperaties anticiperen door meer risico te nemen, wordt de daadwerkelijke redding gereduceerd tot de uitbetaling van een subsidie die banken reeds in hun bedrijfsmodel en risicobeheersing hebben verdisconteerd. Dit soort garanties ondermijnt de disciplinerende werking van financiële markten en legt de kiem voor een nieuwe financiële crisis.

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