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Christian Witt

Essays on Real Estate and Financial Crisis

From the US Housing Market Downturn to the Global Financial Crisis

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Christian Witt
Regensburg, 28 May 2014

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List of Acronyms

ABCP	Asset-Backed Commercial Paper: A short-term security backed by a pool of financial assets. Maturities range up to 270 days. Typical collateral involves mortgages, credit-card receivables, leases, royalties, car or student loans.
ABS	Asset-Backed Security: A security backed by a pool of financial assets other than real estate and mortgages. Typical collateral involves credit-card receivables, leases, royalties, car or student loans.
AuM	Assets under Management.
BBA	Britisch Bankers Association.
CDO	Collateralised Debt Obligation: A structured financial product used to repackage and securitise other financial assets. Typical collateral involves asset-backed securities, corporate loans, leveraged loans, mortgage-backed securities, or project finance debt.
CDS	Credit Default Swap: A swap agreement designed to offer the buyer an insurance against the default risk of an underlying asset. Under the agreement the seller compensates the buyer in the event the underlying loan experiences a pre-defined credit event. The buyer periodically pays a premium in return, unless a credit event takes place.
DCC	Dynamic conditional correlation.
DCCX	Dynamic conditional correlation including exogenous variables.
Factor DCCX	Factor dynamic conditional correlation including exogenous variables.
FRBNY	Federal Reserve Bank of New York.
GARCH	Generalised autoregressive conditional heteroskedasticity.
IMF	International Monetary Fund.
LIBOR	London Interbank Offered Rate.
LTCM	Long-Term Capital Management.
LTV	Loan-to-Value ratio: A financial ratio used in the real estate sector. It illustrates the leverage a debtor obtains by borrowing against a property.
MBS	Mortgage-Backed Security: A security backed by a pool of mortgages or other real estate loans.
MSCI	Morgan Stanley Capital International.

Repo	Repurchase Agreement: A financial transaction designed to facilitate borrowing against other liquid securities, such as government bonds or equities. Under the agreement the original seller promises to later buy back the security at a pre-defined higher repurchase price. This way the transaction effectively constitutes a fixed-rate secured loan, where the seller functions as the borrower and the buyer as the lender.
SIFI	Systemically Important Financial Institution: A bank, insurance or other financial institution whose "insolvency would have a serious impact on the functioning of the domestic financial system or significant parts thereof, and would also have negative effects on the real economy" (Bundesbank: http://www.bundesbank.de/Navigation/DE/Service/Glossar/Functions/glossar.html?lv2=129548&lv3=146026)
UK	United Kingdom.
US	United States of America.
VEC	Vector error correction.

Preface

> "Is [the recent mortgage slowdown] a mere irritant in America's vast economy, or the start of something much worse? Opinion on Wall Street is divided. Most argue that the mortgage mess, though a blight on anyone caught up in it, will not spread. The number of mortgages at risk is too small for defaults to threaten everyone else."
>
> *The Economist*, "Cracks in the façade", 22 March 2007.

If you were to ask an economist what the period 2007 to 2009 was all about, the probable answer would be that this was the time of the Global Financial Crisis, one of the most severe episodes of financial stress since the Great Depression. The respondent would be likely to continue that it all started with plummeting house prices in the US, which first spilled over into global interbank markets before triggering a near-meltdown of the world financial system. The repercussions eventually caused many economies around the globe to fall into a sharp recession.

This condensed résumé portrays today's reading of the Global Financial Crisis very well. However, as with every summary, it hides some of the underlying stories that add up to the bigger picture. This is why this dissertation project seeks to address three elements of the chain of events that might deserve more careful attention. The selection is driven by one key question: how could a downturn in a rather small segment of the US housing market turn into a large-scale global financial crisis? In other words, the common theme of the analysis is the dissemination of the economic source shock across markets and regions. For reasons of clarification we distinguish three major phases of propagation: (i) the spreading from the US "subprime" housing market to the country's entire residential real estate market; (ii) the proliferation across large banks and investors via secured money markets; and (iii) the dissemination of financial turbulence across domestic financial sectors.

The first and barely noticed sign of an imminent crisis appeared in September 2006. The prices of US residential houses had just started to slide, in particular in the so-called "subprime" market. This segment is characterised by the typically lower creditworthiness and higher leverage of homeowners compared with the traditional "prime" segment (cf. Frame et al., 2008; Mian et al., 2009; Demyanyk and van Hemert, 2011). In many cases, the original decline drove market prices below the value of outstanding mortgages (Duke, 2012). Since residential mortgages are mostly non-recourse in the US, the affected homeowners had an incentive to default on their obligations voluntarily (Harris, 2010). This incentive unfolded a wave of uncoordinated foreclosures. A vicious circle ensued, in which lower prices led to higher foreclosures, which reinforced the initial price drop (cf. Campbell et al., 2011; Frame et al., 2008; Mian et al., 2014). At this point, the downward spiral spilled over and harmed the prices of unforced sales (Campbell et al., 2011) in the "prime" segment. These homeowners chose to postpone a sale in order to preserve their long-run profitability. Hence, the overall home sales including both "prime" and "subprime" became increasingly dominated by the worst-performing segment (cf. Wall Street Journal, 2009; CoreLogic, 2010). Chapter 1 examines the observed market dynamics from a game-theoretical perspective. The developed model explains several stylised facts of the recent US housing market crash. The analysis concludes that homeowners usually postpone home sales during a market downturn to escape its negative consequences. However, the typical non-recourse financing of residential real estate in combination with high leverage temporarily damaged the usual market mechanism. This paved the way for the subsequent nationwide housing crisis. On the other hand, the interventions policy makers pursued to find a way out of the crisis (e.g. loose monetary policy, financial stimuli, urban planning) are consistent with the attempt to restore this mechanism.

How could turmoil in the US housing market spread further towards financial markets? Recent research guides us to look into short-term secured funding markets (cf. Brunnermeier, 2009; Gorton and Metrick, 2012): with house prices deteriorating, short-term obligations holding houses as collateral lost value, too. Short-term secured funding was squeezed as a result in the autumn of 2007 (Brunnermeier, 2009). Given the material dependence of market participants on this funding source prior to the crisis (cf. Allen and Carletti, 2008; Gorton and Metrick, 2012), the implications for this and related market segments were grave. The borrowing rates peaked, thereby aggravating the initial funding problems while creating further uncertainty and scepticism among the market participants with respect to the creditworthiness of their counterparties (cf. Allen and Carletti, 2008; Brunnermeier, 2009; Taylor and Williams, 2009; Gorton and Metrick, 2012;). Hedge funds and prime brokers are traditionally the key players involved in short-term securities borrowing and lending (Gorton and Metrick, 2012). The analysis of Chapter 2 therefore concentrates on the consequences of adverse shocks for this particular financial intermediation chain. The results demonstrate that the intermediation activity diminished significantly in periods of exceptionally high levels of uncertainty. The reduction itself seems to have been driven primarily by the securities hoarding of prime brokers trying to preserve their liquidity position. On top of this, rises in prime brokers' securities holdings show the most devastating impact on financial intermediation activity among all the investigated shocks. Hence, the turmoil in the US housing market spread to short-term funding markets through plummeting collateral values, which caused prime brokers to build up precautionary security buffers at the cost of impaired financial intermediation activity.

After the collapse of the investment bank Lehman Brothers on 15 September 2008, the financial turmoil that had recently been limited to money markets suddenly spilled over and endangered entire domestic financial sectors around the globe (cf. Brunnermeier, 2009;Eichengreen et al., 2009; Bekaert et al., 2014). The Global Financial Crisis was born. Chapter 3 investigates the sources of this unanticipated and forceful global propagation of financial turbulence. As the analysis reveals, even elaborate factor asset pricing models are insufficient to describe the most severe episodes of the Global Financial Crisis. Further taking into account continuous time-dependent co-movement patterns adds precious information. Not only does it help to identify contagion—defined as residual co-movement unaccounted for by fundamentals—, but it also allows us to quantify its magnitude and to detect timing patterns. Indeed, contagion spread financial turmoil to most examined countries only after the investment bank Lehman Brothers dissolved. It was also forceful as the average size was 16.3% in terms of unconditional correlations. A closer examination of what lies behind contagion reveals that US and global shocks are the primary sources of excessive co-movement. By contrast, domestic and residual shocks consistently abate the extent of contagion. Hence, similar to the tumbling house prices that had previously spooked secured money markets, contagion undermined domestic financial sectors worldwide, thereby eventually bringing the Global Financial Crisis to a peak.

The three events investigated in this thesis are indispensable for understanding some of the key economic forces that supposedly lay behind the escalation of the Global Financial

Crisis. They tell a story of what went wrong and why. For instance, had mortgage contracts not been "ill-designed" in the sense that they facilitated deliberate defaults, the drag on the wider US housing market would have been less dramatic. Had large financial institutions not relied that heavily on short-term funding backed by US housing collateral, they might have been able to sufficiently roll over their obligations. Had the hoarding of liquid securities by prime brokers not harmed financial intermediation, the secured funding market might not have squeezed. Consequently, Lehman Brothers would perhaps have been intact today. No financial contagion would have been released. But unfortunately, all of these events did occur. Nonetheless, this experience gives policy makers, professionals and researchers the opportunity to learn how comparable episodes of turbulence might be better coped with. Therefore, studying the individual stories of the Global Financial Crisis that add up to the bigger picture is crucial for the future.

Chapter 1

On Housing Market Downturns and Optimal Seller Behaviour

Abstract

Housing market downturns typically clear through home sales rather than prices, since homeowners tend to postpone a sale to avoid fire sale prices. The experience of the 2006-2009 US housing crisis challenges this paradigm. We develop a housing market model that allows downturns to unwind through home sales or prices by linking the severity of slowdowns to the timing of home sales by homeowners and the market clearing. Homeowners are heterogeneous, rational and profit-maximising. House prices plummet, only if a sufficiently large housing overhang compromises their sales strategy. The model explains several stylised facts of the recent US housing crisis.

1.1 Introduction

A widely shared economic paradigm states that house prices are downwardly sticky (cf. Leamer, 2007; Case, 2008; Case and Quigley, 2008; Lazear, 2010). In this reading, housing downturns are better characterised by slowing home sales and soaring housing inventory. Case (2008) called this the "quantity clearing mechanism". Earlier empirical evidence seemingly confirmed this perception. After the Great Depression when an eight-year housing recession finally came to halt in 1933 (-30.5%), house price declines became increasingly rare. Besides, housing downturns resulted merely in mild price depreciations, if any, between 1945 and 2006. The largest drop in national house prices did not exceed 2.9% on a year-to-year basis.[1] Instead housing downturns unwound through receding housing starts (Case, 2008) and humble residential investment (Leamer, 2007). Even regional housing market slowdowns tended to clear this way, as the example of the "first California boom" from 1975 to 1980 illustrates (Case and Quigley, 2008). Survey evidence (cf. Case and Shiller, 1988, Case et al., 2003, Case et al., 2012) further consistently suggested that homebuyers would respond to the sluggish demand by retarding their sales rather than lowering their asking prices.[2] This led to the emergence of a paradigm that Ben Bernanke so famously concluded (CNBC, 1 July 2005): "We've never had a decline in house prices on a nationwide basis. So, what I think what is more likely is that house prices will slow, maybe stabilise, (...)."

The US housing market crash between 2006 and 2009 challenges the traditional paradigm, as house prices collapsed outright over the course of this crisis, giving rise to a "price clearing mechanism". From peak to trough, the S&P/Case-Shiller National House Price Index plummeted by roughly 32.0% (a later decrease added another 3.8%), which translates into a compound annual growth rate of -13.1%. This was the most violent house price correction ever documented in the US. The eight-year housing recession that extended into the Great Depression saw house prices depreciate by merely 4.4% per year. Even more intriguingly, despite a simultaneous nosedive of 41.0% in home sales, house prices depreciated even faster for a large part of the crisis (see Figure 1.1). Only in the early phase

[1] The historical house price data stem from Robert Shiller's website: www.econ.yale.edu/ shiller/data/Fig2-1.xls. The author uses the Grebler House Price Index and the S&P/Case-Shiller National House Price Index. For details, please consult his seminal work "Irrational Exuberance" (Shiller, 2009).

[2] In a related survey study, Blinder (1982) found evidence of producers of durable goods responding to excess supply by increasing their inventories.

(Q2/2006 to Q3/2007) home sales declined quicker than house prices (26.6% vs. 5.2%). Following a brief transition phase (Q3/2007 to Q1/2008) when both decreased roughly at the same rate (10.4% vs. 10.9%), house prices growth outpaced home sales (4.4% vs. 15.9%) in the final phase of the crisis. The paradigm of primarily quantity-driven market clearing is therefore difficult to justify. Instead, the US housing market crash calls for a complementary "price clearing mechanism".

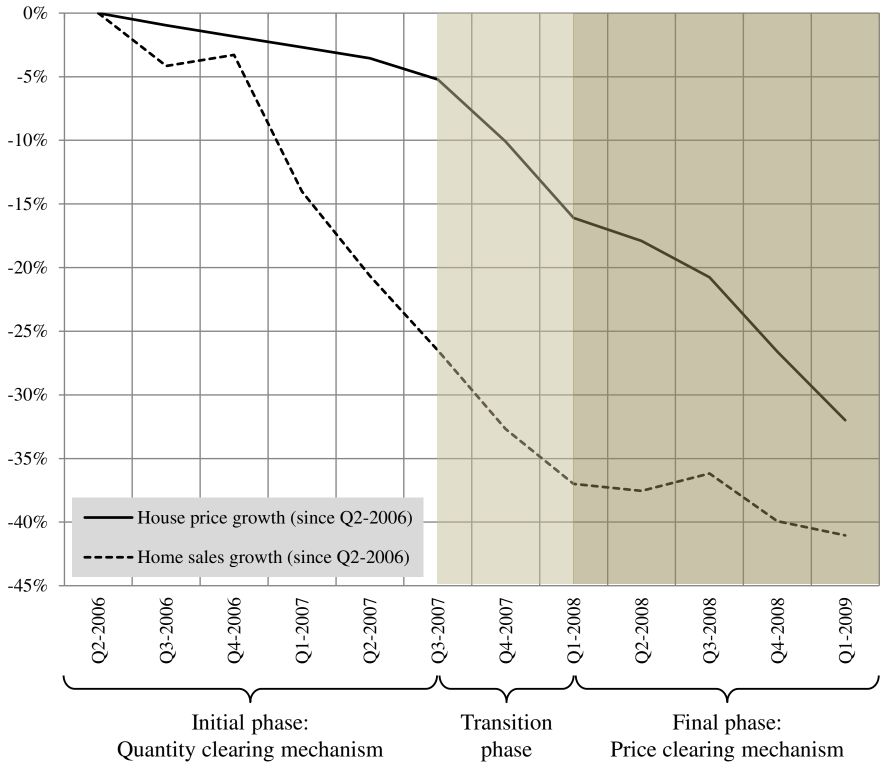


Figure 1.1: US house prices and home sales from peak to trough (Q2/2006 to Q1/2009). This figure illustrates the evolution of US house prices and home sales from peak to trough during the recent US housing market crash (Q2/2006 to Q1/2009). In the initial phase of the crisis, home sales decline steeper than house prices. Over the transition phase both depreciate at roughly the same rate. In the final phase of the crisis, the decline in house prices exceeds the one in home sales. Growth rates are computed since inception of the crisis (Q2/2006) based on the S&P Case/Shiller National House Price and existing home sales, respectively. Data sources: Robert Shiller (www.econ.yale.edu/shiller/data/Fig2-1.xls), National Association of Realtors.

This fresh evidence reveals a major gap in the theoretical housing literature. Most existing housing market models fail to account for material price drops. For they are designed in accordance with the "quantity clearing mechanism". In this reading, homeowners avoid marketing their homes during housing downturns for various reasons. Some models attribute their reluctance to sell to matching issues (cf. Wheaton, 1990; Williams, 1995; Glower et al., 1998; Albrecht et al., 2007; Chernobai and Hossain, 2012) and others to downpayment constraints (cf. Stein, 1995; Genesove and Mayer, 1997), loss aversion

(Genesove and Mayer, 2001) or anchoring (Bokhari and Geltner, 2011). One notable exception from the mainstream is Qian (2013) who argued in favour of an embedded real option in housing. Another exception is Lazear (2010). The author took the position that homeowners set asking prices strategically to determine the probability of a sale, because they enjoy some monopolistic power. However, all of the above approaches focus *a priori* on the supply of houses as the predominant factor in the housing market. A theory comprehensive enough to explain material falls in house values or even a reversal of the market clearing mechanism is so far lacking.

In this paper, we therefore develop a novel game-theoretical rationale that features sticky house prices ("quantity clearing mechanism") during some housing downturns and major price drops ("price clearing mechanism") during others. The connecting element is the optimal sales strategy of leveraged homeowners. In simplified terms, homeowners possess two options: they either sell immediately at potential fire sale prices or they postpone a sale until their mortgage matures to sit out the negative consequences of the slowdown.[3] The best response arguably depends on the severity of the slowdown. Homeowners are inclined to retard a sale under low to moderate excess supply, because the present value of the future sales price plus rent income tends to exceed the immediate short-term house price. However, they lose any interest in delaying a sale strategically once a sufficiently large overhang destroys the home value at maturity. The subsequent uncoordinated sell-off of houses allows prices to plummet in the short term. The model consequently establishes a causal link between the severity of slowdowns, the timing of home sales by homeowners and the way in which housing markets clear.

However, homeowners face a non-trivial decision problem. On one side, they possess some monopolistic power, because housing is durable. They might even postpone a sale for years. This obviously shifts the negotiation power in their favour during market downturns. In fact, their situation is reminiscent of a durable good monopolist, who can freely set the offered quantity.[4] On the other side, there are limitations to this strategic behaviour. First, homeowners face external competition as well as rivalling

[3] Comparable decision problems relate to the non-participation in labour markets (Murphy and Topel, 1997) or the dynamic pricing of durable goods (Blinder, 1982). Lazear (2010) implicitly pointed in the same direction.

[4] In his seminal paper, Coase (1972) conjectures that such a monopolist cannot profit from market power due to time inconsistency. However, extensive research shows ways out of this dilemma, e.g. by monopolizing the after-market, product differentiation or planned obsolescence. For an overview refer to Belleflamme and Peitz (2010).

other incumbents in an oligopolistic fashion. Second, prospective homebuyers, too, gain bargaining power during a market slowdown due to the emergence of excess housing supply. Third, homeowners need to take out a mortgage to finance their initial investment in a similar way to any other capital-intensive durable good. Once their mortgage expires, homeowners are forced to sell (or, equivalently, rollover their mortgage) at the then-house prices. Fourth, homeowners will not postpone a sale, if the short-term house price exceeds the present value of a postponed sale plus rent income. After all, homeowners face a multi-dimensional optimization problem when assessing their best response to a housing downturn.

The presented model examines the optimal sales strategy of homeowners in a framework tailored to accommodate the specifics of housing. The envisioned housing market is segmented. This reflects the market's heterogeneity across homeowners and regions in reality. Homeowners vary by age, creditworthiness, cultural background, gender, income or marital status. Regions differ by density, infrastructure or macro-economic conditions. Moreover, homeowners are rational and profit-maximising. They do not suffer *a priori* from behavioural biases such as loss aversion (Genesove and Mayer, 2001) or anchoring (Bokhari and Geltner, 2011). Homeowners further need to take out a mortgage to finance the initial purchase of a house as houses are highly capital-intensive. Similar financial restrictions are imposed by Stein (1995), Genesove and Mayer (1997) and Brueckner et al. (2011). Finally, the model mimics some of the key characteristics of the US housing market: the market is divided among prime and subprime homeowners, their leverage matches realistic levels, and borrowing is non-recourse (cf. Frame et al., 2008; Harris, 2010, Gao and Li, 2013). The heterogeneous model accordingly portrays various specifics of the housing market.

The simulations of the heterogeneous housing model deliver rich insights. Above all, homeowners may stabilise or compromise house price growth depending on the severity of the slowdown. On one hand, homeowners support short-term house prices by strategically postponing home sales to preserve their medium-term financial interests. The consequent reduction in home sales eventually stabilises the short-term price. On the other hand, as soon as a sufficiently large overhang harms the medium-term financial interests of homeowners their willingness to retard a sale vanishes. This may elicit uncoordinated sell offs spilling over to the competing segment and impairing the short-term house price. Besides, a segmented housing market is more resilient to low and moderate oversupply, but more vulnerable to substantial overhangs. This is because cross-segment competition provides homeowners with leeway for responding strategically even to segment-specific downturns. But it also impairs the overall market depth and thus the capacity to absorb substantial overhangs. Hence, the way in which a market clears depends on its fragmentation and on the severity of the crisis: Low to moderate excess supply results in a "quantity clearing mechanism" and a substantial overhang of houses in a "price clearing mechanism".

Furthermore, a model version accounting for deliberate defaults of homeowners, a lack of available lending volume and other US-specific aspects, well explains several stylised facts of the US housing market crash from 2006 to 2009. The model projections are compatible with the observed house price growth, its negative correlation with foreclosures (Frame et al., 2008), the concentration of foreclosure in the subprime segment (cf. Mian et al., 2009; Demyanyk and van Hemert, 2011), and the built-up in housing inventory (cf. CoreLogic, 2010; Lazear, 2010). Most notably, both the observed and projected house prices exhibit a "double drop"—two briefly interrupted consecutive slides. In the model, house price drops occur whenever homeowners deliberately default on their mortgages. The subsequent sell-off of foreclosed homes damages house prices in both segments. Therefore, the negative correlation between house price growth and foreclosures. Besides, subprime homeowners are the first to default since they are particularly leveraged and worst affected by the downturn. This explains the concentration of foreclosures in the subprime segment. The nonetheless material housing inventory is either due to a strategic shortage of prime houses or the *inefficient* and *harmful* crowding-out of non-distressed home sales as a result of lacking lending volume. Thus, a model customised to reflect the specifics of the US housing market well explains several stylised facts of the country's devastating recent housing crisis.

The rest of the paper is organised as follows. Section 1.2 outlines the fundamental game-theoretical idea in a homogeneous setting. This model version is best suited to elucidating the primary dynamics, despite its overly simplistic structure. It also serves as a benchmark later on. Next, Section 1.3 cultivates the analysis in a more realistic heterogeneous framework. Section 1.4 simulates both model versions and compares the numerical results. Subsequently, we investigate how varying inputs affect the heterogeneous model. Section 1.5 revisits the recent US housing market crash (2006-2009). We refine the heterogeneous model in such a way that it portrays the key characteristics of the country's housing market at the time: most notably its prime and subprime segments. Finally, we conclude and briefly discuss the policy interventions in the housing market throughout Section 1.6.

1.2 Homogeneous Housing Market

We initially describe the decision problem of homeowners in the least complex setup. Housing, homeowners and prospective homebuyers are all homogeneous. Later on, housing will become heterogeneous.

1.2.1 Static Equilibrium

Suppose a *competitive* housing market populated by $i \in 1, ..., n$ homogeneous and profit-maximising homeowners, each owning one unit of identical housing worth p. The housing stock is consequently similar to the number of homeowners, $h = n$. However, since not all houses must necessarily trade on the market, home sales, $x \geq 0$, may be smaller than the housing stock, $h \geq x$.

Homeowners invest in housing to realise positive returns over the investment horizon, T, so they need substantial external financing to raise the purchase price (cf. Brueckner et al., 2011). For simplicity, they take on a 100 percent mortgage with a constant interest rate, r, and the same maturity as the investment horizon. Both the principal and the compound interest are due at redemption. The terminal balance due equals $p(1 + r)^T$ accordingly. On the other hand, homeowners earn income from their property. For one thing, they realise or save periodical rent, ωp, which is directly proportional to the house price, $\omega \in (0, 1)$.[5] By reinvesting the proceeds until maturity, homeowners further accumulate capital gains of $I(T) = \sum_{k=1}^{T}(1 + r)^k$ so that the capitalised rent income amounts to $\omega pI(T)$.[6] For another thing, homeowners sell their house at redemption and earn p. Thus, they have funds of $p\big(1+\omega I(T)\big)$ at hand to settle their outstanding liabilities

[5] This formulation allows me to express that the amount of rent and the house price are typically tied to one another (Gallin, 2008).

[6] $I(T)$ follows a geometrical sequence, $I(T) = \sum_{k=1}^{T}(1 + r)^k = [1 - (1 + r)^{T+1}]/[1 - (1 + r)] > 0$.

eventually. Equation 1.1 summarises the investment motive:

$$p\big(1+\omega I(T)\big) \geq p(1+r)^T. \tag{1.1}$$

An important corollary is that the fraction of the house price that homeowners periodically extract as rent must never violate $\omega \geq \big((1+r)^T - 1\big)/I(T)$ to be compatible with the investment motive. In addition, the amount of rent entirely depends on the interest rate and maturity of the mortgage.

Homeowners obtain the needed funding from banks. The banking sector is homogeneous and handles all mortgages. In the tradition of Diamond (1984) and Holmstrom and Tirole (1997), the lending costs comprise the loan volume and monitoring efforts. The aggregate lending volume of the banking sector, lx, is proportional to the individual loan volume, $l \geq 0$, and the number of home sales, x. Furthermore, monitoring efforts contain a fixed component, $\nu > 0$, to cover the administrative expenses and a variable transaction-linked component, $\phi > 0$. In economic terms, ϕ is similar to an agio being paid by borrowers for the service of financial intermediation. The resultant total costs of the banking sector amount to $lx + \nu + \phi x$, while the marginal lending costs are $l + \phi$. To keep matters simple, the individual loan volume, l, is standardised to one, $l = 1$.

Prospective homebuyers have the following inverse demand function, which decreases linearly in home sales:

$$p = \alpha - \beta x, \tag{1.2}$$

where $\alpha > 0$ denotes the reservation price and $\beta > 0$ the supply elasticity. In a competitive market, participants have no bargaining power (cf. Belleflamme and Peitz, 2010). The good is supplied at marginal costs, $p^* = 1+\phi$, and the entire housing stock is for sale, $h^* = x^*$. Substituting these two expressions in Equation 1.2 yields the long-run equilibrium housing stock:

$$h^* = \frac{1+\alpha-\phi}{\beta}. \tag{1.3}$$

Both the long-run equilibrium house price, $p^* = 1+\phi$, and the housing stock, $h^* = (1+\alpha-\phi)/\beta$, play a pivotal role in the subsequent discussion on housing market downturns.

1.2.2 Housing Market Downturns

We define a housing market downturn as a situation of excess supply, i.e. when the existing housing stock exceeds the level that is sustainable in the long run. Since the housing stock barely adjusts in the immediate short term (cf. Case, 2008; Leamer, 2007)—the typical depreciation rate, $\delta \geq 0$, is merely about 1.9% (Harding et al., 2007)—even small declines in the demand might drag house prices below their long-run level. On the other hand, homeowners have the option to postpone home sales to a later date, thereby resisting some of the downward pressure. Therefore, how should homeowners respond to housing market downturns and how does their behaviour affect the house price in the immediate short term?

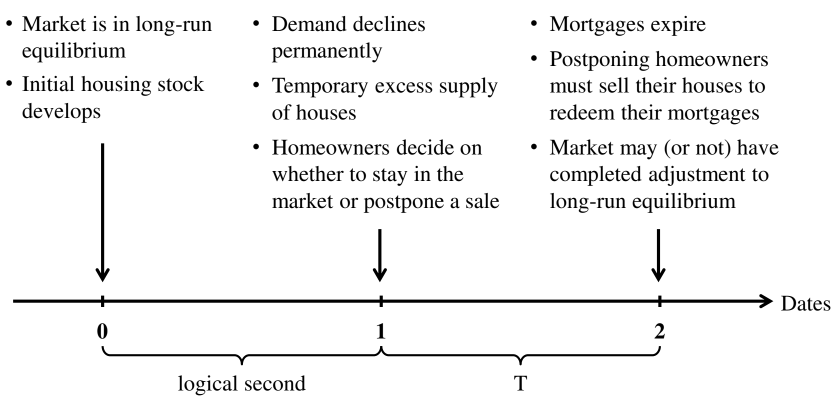


Figure 1.2: Course of events. This figure illustrates how a market downturn evolves in the model. Time between dates is not equidistant.

In order to characterise the reaction of homeowners to market downturns, we illustrate their decision problem in a dynamic setting (cf. Figure 1.2). The game proceeds on three dates, $t = 0, 1, 2$, and the time between them is not equidistant. To distinguish between dates, we add corresponding subscripts to all the time-dependent parameters and variables.

On date 0, the market is in long-run equilibrium. The long-run equilibrium house price accordingly equals $p_0^* = 1 + \phi$ with housing stock $h_0^* = \big(\alpha_0 - (1 + \phi)\big)/\beta$. On date 1, a logical second later, an exogenous shock permanently decreases the homebuyers' reservation price by $\varepsilon \in (0, 1)$ percent to $\alpha_1 = \alpha_0(1 - \varepsilon)$.[7] As a consequence, the new

[7] The assumption of a permanent decline of housing demand is meant to reflect existing rigidities in housing markets. For instance, even eight years after the start of the US housing crisis demand for

housing stock that is sustainable to the long run reduces to $h_1^* = \big(\alpha_1 - (1+\phi)\big)/\beta$ and creates an oversupply of houses in the amount of $\Delta h_1 = h_0^* - h_1^*$. This oversupply lasts until continuous depreciation, $T\delta h_0^*$, eliminates it over time. However, the new long-run equilibrium house price remains unchanged since the marginal costs stay the same, $p_1^* = 1 + \phi$. Short-term home sales, x_1, and the house price, p_1, are unknown for the time being as the sales decision of homeowners is pending. On date 2, T periods later, all mortgages expire since lenders demand repayment. All homeowners have to sell their properties eventually, independent of the prevalent market conditions. Thus, the entire housing stock is for sale, $x_2 = h_2$, and the then-house price equals $p_2 = \alpha_1 - \beta h_2$. In the best case, all of the earlier excess supply has disappeared, $h_2 = h_1^*$. Then, homeowners sell their property without a loss at the long-run equilibrium house price. However, if the housing stock remains elevated, $h_2 = h_0^*(1 - T\delta) > h_1^*$, they will realise a house price below the long-run equilibrium level. The housing stock can be described as $h_2 = \max\big\{h_1^*, h_0^*(1 - T\delta)\big\}$. Figure 1.3 portrays the market dynamics.

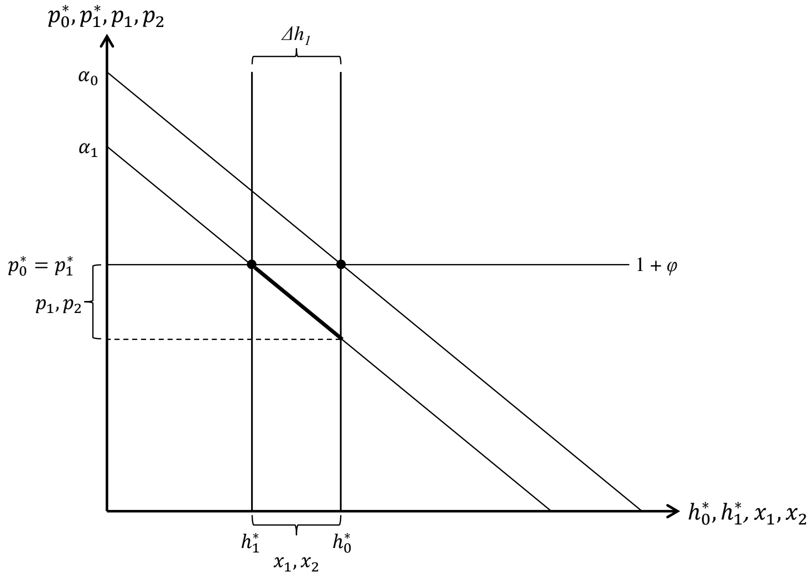


Figure 1.3: Housing market dynamics. This figure portrays demand and supply of housing over time. Demand permanently declines. Marginal costs are constant. Housing supply is fixed in the short-term, but elastic in the long-run. Two bold dots define the original and new long-run equilibrium allocations. The bold line denotes the set of potential short-term allocations.

This situation strongly affects the bargain between incumbent homeowners and prospective homebuyers. On one side, the excess supply temporarily frees homeowners from

houses remains below historical levels. Nonetheless, it is noteworthy that the extent of the housing downturn—and thus its impact on the behaviour of homeowners and house prices—would be smaller, if the initial demand shock were to be temporary in nature.

external competition, because building new dwellings is unprofitable as long as the oversupply exists. Therefore, homeowners enjoy some, though limited room for manoeuvre. Simply put, they either sell immediately at potential fire sale prices, or they postpone a sale until the overhang reduces and the sales prices recover. On the other side, the excess supply lends homebuyers bargaining power to beat down prices, but their bargaining power vanishes over time as the oversupply is highest immediately after the demand declines, since the oversupply dissolves over time. Since both homeowners and homebuyers profit to some extend from oversupply the outcome of the bargaining struggle is ambiguous.

To resolve this conundrum, homeowners maximise their individual immediate short-term profits, $\pi_1^i(p_1, x_1, c)$, depending on the house price, p_1, home sales, x_1, and opportunity costs, c.[8] Opportunity costs depend on the benefits and costs of the two strategic options: selling immediately or postponing a sale. If homeowners sell immediately, they realise the short-term market price p_1 plus first-period rent ωp_0. This amounts to $(p_1 + \omega p_0)(1+r)^T$ at maturity including compound interest. However, this comes at the cost of foregoing the late market price p_2, first-period rent ωp_0, and subsequent periodical rent income proportional to the late price, ωp_2.[9] Including interest earnings this equals $p_2(1+\omega I(T-1)) + \omega p_0(1+r)^T$ at redemption. In both cases, homeowners face an identical amount of repayment costs $p_0(1+r)^T$ and constant transaction costs $\lambda \geq 0$. Condition 1.4 summarises the trade-off between the two options:

$$\underbrace{(p_1 + \omega p_0)(1+r)^T - p_0(1+r)^T - \lambda}_{\text{capitalised net earnings of immediate sale}(t=1)} \geq \underbrace{p_2(1+\omega I(T-1)) + \omega p_0(1+r)^T - p_0(1+r)^T - \lambda.}_{\text{capitalised net earnings of postponed sale }(t=2)} \tag{1.4}$$

Homeowners only sell immediately, if the short-term price outweighs at least the proceeds to be realised until redemption. Otherwise, they postpone a sale. Solving Equation 1.4

8 Departing from typical definitions, costs in this particular context refer to opportunity costs rather than marginal costs, because the latter form sunk costs from a homeowner's point of view. Homeowners have already bought their house at the original long-run equilibrium house price. These earlier expenses do not affect the pending sales decision of homeowners. What really matters is the present value of a postponed sale which homeowners forego were they to sell immediately.

9 Rent income is proportional to p_2 so that rent contracts reflect a potentially depressed late price: $p_2 \leq p_1^*$.

for the short-term price p_1 accordingly returns the opportunity costs of an immediate sale,

$$c = \frac{1}{(1+r)^T}\big(1+\omega I(T\ -1)\big)p_2 \geq 0, \quad \lim_{p_2 \to 0} c = 0. \tag{1.5}$$

The opportunity costs equal the present value of the capitalised net proceeds, if homeowners were to postpone their sales.

Meanwhile, short-term home sales x_1 depend on external and internal competition, as well as the participation of homeowners. External competition ensures that the house price never exceeds the marginal costs in the immediate short-term. This implies that homeowners cannot drive home sales below the new long-run equilibrium housing stock, $x_1 \geq h_1^*$. Otherwise, external investors would seize the profitable opportunity to construct new homes. The bargaining power of homeowners is therefore entirely linked to the oversupply, Δh_1. Internal competition further limits the influence homeowners have on short-term home sales. Let $s \in (0,1)$ denote the *share* of the offered oversupply. Due to the assumed distribution of houses each homeowner controls an equal stake, s^i, of this share. The remainder, s^{-i}, is commanded by the $n-1$ competitors: $s = s^i + s^{-i}$. So, homeowners have merely humble effect on bargaining power. Also, the participation of homeowners is conditional. For homeowners only participate as long as the house price at maturity is positive, $p_2 > 0$. Otherwise, $p_2 = 0$, they sell anyway, $s = 1$, because houses neither have a short-term nor a medium-turn value. After all, external (h_1^*) and internal competition ($\Delta h_1 s^{-i}$) as well as the conditional participation of homeowners (s) considerably influence short-term home sales, $x_1 = h_1^* + \Delta h_1(s^i + s^{-i})$.

This leads us eventually to the optimization problem of homeowners. They maximise their individual short-term profits, $\pi_1^i = (p_1 - c)\Delta h_1 s^i$, taking these factors into account:

$$\begin{aligned} \arg\max_{s}\ & \pi_1^i = \big(\alpha_1 - \beta x_1 - c\big)\Delta h_1 s^i \\ & \text{s.t.}\ \ s \in (0,1), \\ & \qquad p_2 > 0, \end{aligned}$$

where $x_1 = h_1^* + \Delta h_1(s^i + s^{-i})$ denotes short-term home sales. Differentiating with respect to s^i yields a homeowner's reaction function:

$$s^i = \frac{1}{2\beta\Delta h_1}\big((1+\phi) - \beta\Delta h_1 s^{-i} - c\big). \tag{1.6}$$

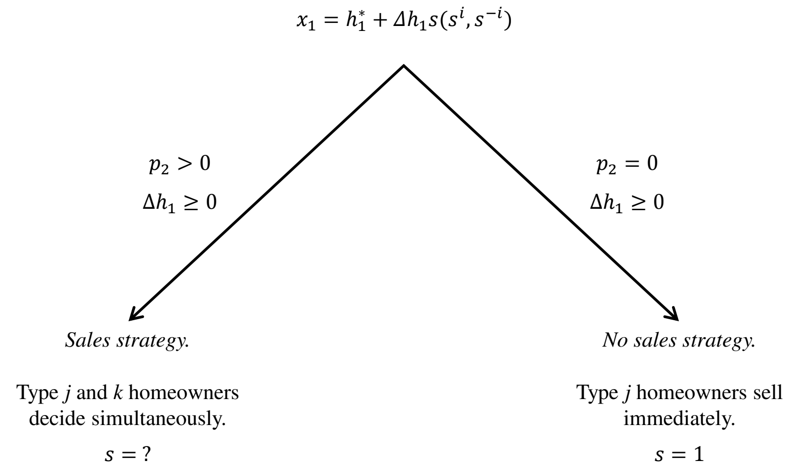


Figure 1.4: Decision problem in a homogeneous housing market. This figure portrays the decision problem of homeowners in a homogeneous housing market in extensive form. Homeowners have an incentive to postpone a sale, as long as houses have an economic value even after retarding a sale, $p_{j2} > 0$. Otherwise, they sell immediately anyway, $p_2 = 0$.

By summing for all n individuals, $\sum_i^n s^i = s$ and $\sum_i^n s^{-i} = s(n-1)$, and solving for s, we obtain the Nash-equilibrium share of the offered oversupply, s^*:

$$s^* = \begin{cases} \frac{n}{(n+1)} \frac{(1+\phi)-c}{\beta \Delta h_1}, & \text{if } p_2 > 0, \\ \\ 1, & \text{if } p_2 = 0, \end{cases} \tag{1.7}$$

provided that $s \in (0, 1)$ lies in the defined area.

Equation 1.7 demonstrates that the willingness of individual homeowners to sell their homes in the immediate short term decreases with the size of the oversupply, Δh_1, and opportunity costs, c. Since opportunity costs in turn decline with growing excess supply, the optimal sales strategy of homeowners remains ambiguous after all, which is why we perform simulations at a later stage to ascertain how different levels of excess supply affect home sales and the house price in the immediate short term.

1.3 Heterogeneous Housing Market

We now generalise our analysis to portray a heterogeneous housing market. In the new setting, homeowners and prospective homebuyers are also heterogeneous as they have different preferences for the different types of housing.

1.3.1 Static Equilibrium

There are two heterogeneous types of competitively traded housing. To distinguish between them we add subscript $j = 1, 2$ to all relevant parameters and variables. The housing market is populated by $i, ..., n_1$ type 1 homeowners and $i, ..., n_2$ type 2 homeowners. The respective housing stock is $h_j = n_j$. Home sales may be lower than the housing stock, $x_j \leq h_j$.

As before, homeowners invest in housing to economise on rent, $p_j\big(1+\omega_j I(T)\big)$. They need external financing for the initial purchase of a house. The funding is bullet so that the balance due at maturity is $p_j(1+r)^T$ including compound interest. Besides, the funding stems from a homogeneous banking sector serving each type of homeowner a customised mortgage to accommodate their specific capital needs, l_j, and monitoring needs, ϕ_j. Thus, the marginal lending costs equal $l_j + \phi_j$. Given the market's competitive nature houses trade at marginal costs, $p_j^* = l_j + \phi_j$.

Prospective homebuyers have the following inverse demand which linearly decreases in home sales of *both* types of housing:

$$p_j = \alpha_j - \beta_j x_j - \gamma_j x_k, \qquad j \neq k. \tag{1.8}$$

$\gamma_j > 0$ is the supply elasticity concerning the competing type of housing. This way, each housing segment experiences cross-segment competition. The house prices are positively correlated via home sales.[10] Thus, even market downturns limited to one housing segment could spread to the other. Since both types of housing are imperfect substitutes the spillover satisfies $\beta_j > \gamma_j$. For $\gamma_j = 0$ homogeneous housing emerges as a special case of Equation 1.8.

Changes in cross-segment competition unwind via home sales. To illustrate this, we rearrange Equation 1.8 and obtain $x_j = (\alpha_j - p_j - \gamma_j x_k)/\beta_j$, $j \neq k$. By substituting the corresponding symmetric expression of x_k into x_j, we illustrate homes sales in terms of

[10] This assumption reflects that the two types of housing, even though they represent different qualities or regions, are to a large degree similar since they serve the same needs. Thus, they should largely underlie similar economic dynamics.

house prices:

$$x_j = \frac{\beta_k\big(\alpha_j - p_j\big) - \gamma_j\big(\alpha_k - p_k\big)}{\beta_j\beta_k - \gamma_j\gamma_k}, \qquad j \neq k. \tag{1.9}$$

This formulation demonstrates that an isolated increase in house prices prompts *ceteris paribus* a substitution effect: If type k housing becomes more expensive (cheaper), type j housing becomes relatively more (less) popular with homebuyers. This is because home sales x_j rise (decrease). Therefore, changes in cross-segment competition dissipate through home sales.

Furthermore, Equation 1.8 allows us to characterise the long-run housing stock. Since both types of housing are traded competitively, houses are supplied at marginal costs, $p_j^* = l_j + \phi_j$, with the entire housing stock being up for sale, $x_j^* = h_j^*$. Thus, the long-run equilibrium housing stock is: $h_j^* = \big(\beta_k(\alpha_j - (l_j + \phi_j)) - \gamma_j(\alpha_k - (l_k + \phi_k))\big)/(\beta_j\beta_k - \gamma_j\gamma_k)$, $j \neq k$. Notice that the new long-run housing stock is always smaller than in the homogeneous case. To see this, imagine that the difference in parameters vanishes (i.e. subscripts disappear) and the loan volume is again standardised to $l = 1$. Then, the long-run housing stock simplifies to $h_j^* = \big((\beta - \gamma)(\alpha - (1 + \phi))\big)/(\beta^2 - \gamma^2)$. Thus, the present and previous housing stock merely differ in terms of $(\beta - \gamma)/(\beta^2 - \gamma^2) \lesseqgtr 1/\beta$. Since $\beta > \gamma$, it follows that $\beta(\beta - \gamma)/(\beta^2 - \gamma^2) < 1$. Hence, $1/\beta > (\beta - \gamma)/(\beta^2 - \gamma^2)$. The intuitive reason for this finding is that heterogeneity interferes with competition since spillovers are imperfect ($\beta_j > \gamma_j$). Accordingly, the home sales are higher when we abstract from heterogeneity.

1.3.2 Housing Market Downturns

In a heterogeneous setting, a market downturn denotes a situation of excess supply in at least one housing segment. The affected homeowners must decide whether to exploit the durability of housing and postpone a sale or not.

Again, there are three dates, $t = 0, 1, 2$, and the dates are not equidistant. To distinguish the dates, we add another subscript to all time-dependent parameters and variables.

The housing downturn evolves in the same way as before. On date 0, the market is in long-run equilibrium. The house prices and home sales accordingly equal their static equivalents: $p_{j0}^* = l_j + \phi_j$ and $h_{j0}^* = \big(\beta_k(\alpha_{j0} - (l_j + \phi_j)) - \gamma_j(\alpha_{k0} - (l_k + \phi_k))\big)/(\beta_j\beta_k - \gamma_j\gamma_k)$,

$j \neq k$. On date 1, a logical second later, the demand for houses declines permanently. To emphasise the heterogeneity of the housing market, the drop in reservation prices $\varepsilon \in (0,1)$ may affect each segment differently depending on the shock co-movement $\rho \in (0,1)$.[11] The new reservation prices are $\alpha_{j1} = \alpha_{j0}(1-\varepsilon)$ for type j houses and $\alpha_{k1} = \alpha_{k0}(1-\rho\varepsilon)$ for type k houses. Type j housing is therefore worst affected by the slowdown. The new long-run equilibrium house prices and home sales become $p^*_{j1} = l_j + \phi_j$ and $h^*_{j1} = \big(\beta_k(\alpha_{j1}-(l_j+\phi_j)) - \gamma_j(\alpha_{k1}-(l_k+\phi_k))\big)/(\beta_j\beta_k - \gamma_j\gamma_k)$, $j \neq k$. Short-term home sales, x_{j1}, and house prices, p_{j1}, are unknown for the time being as the sales decision of homeowners is pending. On date 2, T periods later, all outstanding mortgages expire thereby compelling homeowners to sell their houses. Thus, home sales match the housing stock, $x_{j2} = h_{j2}$. The resultant house prices are $p_{j2} = \alpha_{j1} - \beta_j h_{j2} - \gamma_j h_{k2}$.

However, a housing downturn may unwind very different from before due to cross-segment competition. The latter interferes with the initial size and direction of excess supply, the depreciation dynamics and how homeowners maximise their profits. First of all, a downturn provokes an overhang only in the worst-hit housing segment while the other might even witness a lack of houses because of the cross-segment substitution effect described earlier. If a negative demand shock makes a certain housing segment less attractive, the other becomes *ceteris paribus* more popular. Therefore, only the worst-hit housing segment suffers excess supply in any event, $\Delta_{j1} \geq 0$.[12] What happens to the competing segment k is ambiguous, since the latter is potentially less affected by the demand shock. Type k housing only witnesses an oversupply, $\Delta_{k1} \geq 0$, if the shock co-movement is both positive and outweighs the cross-segment substitution effect, $\rho \geq \gamma_k\alpha_{j0}/\beta_j\alpha_{k0} > 0$.[13] Otherwise, the segment lacks houses, $\Delta h_{21} < 0$. Hence, only the worst-hit type of housing faces an oversupply with certainty during a housing downturn, whereas the other segment may even lack houses.

Second, the cross-segment competition may complicate the depreciation dynamics depending on the initial excess supply. For one thing, if a given segment still suffers a surplus of houses at maturity, $\Delta h_{j1} \geq T\delta h^*_{j1} \geq 0$, the housing stock in the other segment may equilibrate the aggregate housing market, by temporarily depreciating below

[11] We limit the correlation to non-negative values in order to ensure that any housing downturn has at least a tendency to negatively affect the housing market in general.

[12] Under the given assumptions, $h^*_{j0}, h^*_{j1} \geq 0$ and $\alpha_{j0} \geq \alpha_{j1}$. Hence, $h^*_{j0} \geq h^*_{j1}$, so that $\Delta h_{j1} \geq 0$ follows independent of the shock co-movement.

[13] Rewriting the respective excess supply gives $\Delta_{k1} = \varepsilon(\beta_j\alpha_{k0}\rho - \gamma_k\alpha_{j0})/(\beta_j\beta_k - \gamma_j\gamma_k) \geq 0$. Solving the expression for ρ returns the condition.

its long-run equilibrium level. For another thing, if a given housing segment even lacks houses, $\Delta h_{j1} < 0$, it has no need for depreciations at all. We distinguish four scenarios:

$$h_{j2} = \begin{cases} \max\Big\{ h^*_{j1}, h^*_{j0}(1 - T\delta_j) \Big\}, & \text{if } \Delta h_{j1} \geq 0 \quad \text{and} \\ & T\delta_k h^*_{k0} \geq \Delta h_{k1} \geq 0, \\ \max\Big\{ \frac{\alpha_{j1} - (l_j + \phi_j) - \gamma_j h^*_{k0}(1 - T\delta_k)}{\beta_j}, h^*_{j0}(1 - T\delta_j) \Big\}, & \text{if } \Delta h_{j1} \geq 0 \quad \text{and} \\ & \Delta h_{k1} \geq T\delta_k h^*_{k0} \geq 0, \\ \max\Big\{ h^*_{j1}, h^*_{j0}(1 - T\delta_j) \Big\}, & \text{if } \Delta h_{j1} \geq 0 \quad \text{and} \\ & \Delta h_{k1} < 0, \\ \max\Big\{ h^*_{j0}, \frac{\alpha_{j1} - (l_j + \phi_j) - \gamma_j h^*_{k0}(1 - T\delta_k)}{\beta_j} \Big\}, & \text{if } \Delta h_{j1} < 0. \end{cases}$$

Suppose that both markets witness an initial excess supply. (a) If the depreciation in segment k is sufficient to offset the excess supply until maturity, the type j housing stock also moves towards its long-run equilibrium level: $h_{j2} = \max\big\{h^*_{j1}, h^*_{j0}(1 - T\delta_j)\big\}$. (b) However, if the depreciation in segment k are insufficient to balance the surplus, the depreciation dynamic in segment j might temporarily overshoot to compensate for any imbalances on the aggregate level. The only condition is that house prices must not exceed marginal costs: $h_{j2} = \max\big\{\frac{\alpha_{j1} - (1 + \phi_j) - \gamma_j h^*_{k0}(1 - T\delta_k)}{\beta_j}, h^*_{j0}(1 - T\delta_j)\big\}$. Now assume that only one segment suffers oversupply, while the other lacks houses. (c) If this lack of houses materialises in the competing segment k, the type j housing stock gradually moves towards the long-run level: $h_{j2} = \max\big\{h^*_{j1}, h^*_{j0}(1 - T\delta_j)\big\}$. (d) However, if segment j itself lacks houses, its housing stock equilibrates any imbalances on the aggregate level, unless house prices do not exceed marginal costs: $h_{j2} = \max\big\{h^*_{j0}, \frac{\alpha_{j1} - (1 + \phi_j) - \gamma_j h^*_{k0}(1 - T\delta_k)}{\beta_j}\big\}$. As these scenarios illustrate the worst-hit segment guides the adjustment process towards the new long-run equilibrium. The other segment tends to accommodate any imbalances in the aggregate housing stock. Thus, cross-segment competition divides the pressure to adjust among the different housing segments.

Third, the direction of the initial oversupply influences the way in which homeowners maximise their profits during a downturn (cf. Figure 1.5). On one hand, the type j homeowners may consciously waive some of their bargaining power, if their segment lacks houses, $\Delta h_j 1 < 0$, while the competing segment sees an overhang, $\Delta h_k 1 \geq 0$. Then, they await the decision of the type k homeowners and serve the residual short-term housing demand, $x_{j1} = \big(\alpha_{j1} - \gamma_j x_{k1} - (l_j + \phi_j)\big)/\beta_j$, without risking a loss. If, on the other hand, the type j homeowners suffer an excess supply of houses, $\Delta h_j 1 \geq 0$, they maximise their profits by influencing short-term home sales, $x_{j1} = h^*_{j1} + \Delta h_{j1} s_j$, through the share of offered oversupply, $s_j = s^i_j + s^{-i}_j$. Then, we differentiate three cases: (a) Under rare circumstances, the medium-term house price becomes zero, $p_{j2} = 0$, at which point retarding a sale no longer pays out and homeowners sell immediately, $s_j = 1$. (b) Type j homeowners have a first-mover advantage, if the competing housing segment lacks supply, $\Delta h_k 1 < 0$, allowing type k homeowners to waive some of their bargaining power. (c) The type j and k homeowners may decide simultaneously, if both housing segments experience an overhang. As these examples illustrate, the direction of oversupply interferes with the profit maximization of homeowners. After all, the cross-segment competition considerably enriches several model dynamics—initial oversupply, depreciation dynamics and the profit maximization—, allowing housing downturns to unwind very different than before.

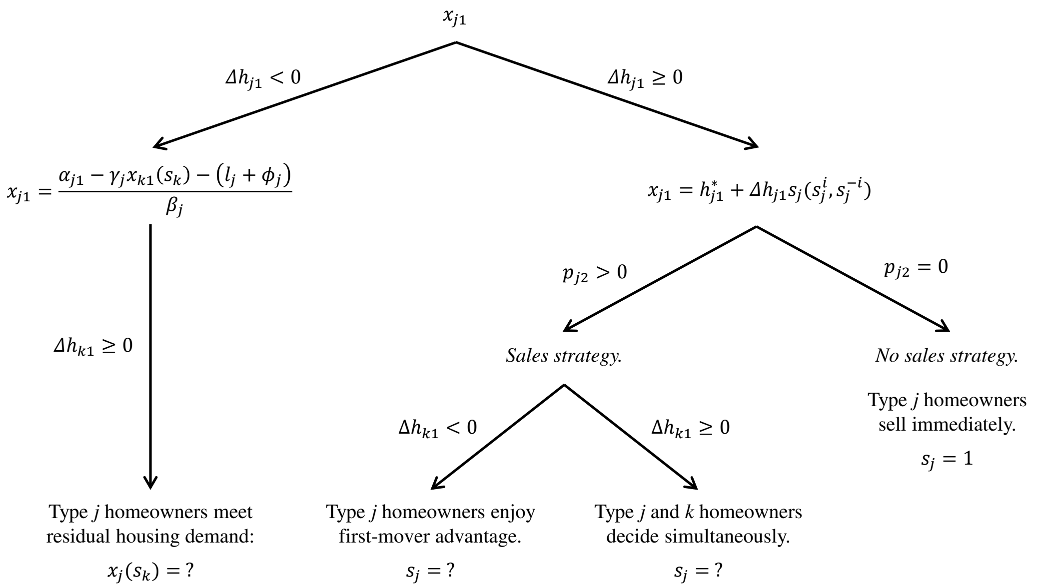


Figure 1.5: Decision problem in a heterogeneous housing market. This figure portrays the multi-layered decision problem of type j homeowners in a heterogeneous housing market in extensive form. Type j homeowners meet the residual demand unsatisfied by the competing type, if their segment lacks houses, $\Delta_{j1} < 0$. Only in the opposite case, $\Delta_{j1} \geq 0$, homeowners may have an incentive to strategically postpone a sale. They only do so as long as houses have an economic value even after retarding a sale, $p_{j2} > 0$. Otherwise, they sell immediately anyway, $p_{j2} = 0$. However, provided that homeowners consider deciding strategically they still face two case dependent options: If the competing housing segment lacks houses, $\Delta_{k1} < 0$, type j homeowners have a first-mover advantage. But if both housing segments suffer an overhang, $\Delta_{k1} \geq 0$, type j and k homeowners make their sales decision simultaneously.

Furthermore, the opportunity costs, c_j, homeowners face with respect to an immediate sale remain as before. Homeowners maximise their profits by weighing the benefits of an immediate sale against those of a postponed one. The benefits of a postponed sale access their decision problem through opportunity costs, c_j. Since the factors behind an immediate home sale—house prices p_{j1} and p_{j2}, rent income $\omega_j p_{j0}(1+r)^T + p_{j2}\omega_j I(T-1)$, balance-due $p_{j0}(1+r)^T$ and transaction costs λ_j—do not change, opportunity costs look as before: $c_j = 1/(1+r)^T\big(1+\omega_j I(T-1)\big)p_{j2}$.

We now turn to characterising the optimal sales decision of homeowners during a downturn in a heterogeneous housing market. The maximization is described from the perspective of an individual type j homeowner. At first, we derive the best responses of homeowners who enjoy a first-mover advantage. This implies that housing segment j suffers an overhang, $\Delta h_{j1} \geq 0$, while the competing segment lacks houses, $\Delta h_{k1} < 0$. Type j homeowners take it as given that competing homeowners offer the residual demand. The corresponding individual optimization problem of a type j homeowner reads:

$$\arg\max_{s_j} \ \pi^i_{j1} = \big(\alpha_{j1} - \beta_1 x_{j1} - \gamma_1 \frac{\alpha_{k1} - \gamma_2 x_{j1} - (l_j + \phi_j)}{\beta_k} - c_j\big)\Delta h_{j1} s^i_j,$$

$$\text{s.t. } \ s_j \in (0,1),$$
$$p_{j2} > 0.$$

Short-term home sales are $x_{j1} = h^*_{j1} + \Delta h_{j1}(s^i_j + s^{-i}_j)$ and $x_{k1} = \big(\alpha_{k1} - \gamma_k x_{j1} - (l_k + \phi_k)\big)/\beta_k$. Differentiation with respect to s^i_j returns a homeowner's reaction function:

$$s^i_j = \frac{\beta_k(\alpha_{j1} - c_j) - (\beta_j\beta_k - \gamma_j\gamma_k)(h^*_{j1} + \Delta h_{j1} s^{-i}_j) - \gamma_j\big(\alpha_k - (l_k + \phi_k)\big)}{2(\beta_j\beta_k - \gamma_j\gamma_k)\Delta h_{j1}} \tag{1.10}$$

On these grounds, the aggregate response of type j homeowners can be found by summing for all n_j individuals, $\sum_i^{n_j} s^i_j = s_j$ and $\sum_i^{n_j} s^{-i}_j = s_j(n_j - 1)$, and solving for s_j:

$$s^*_j = \frac{n_j}{(n_j+1)} \frac{\beta_k(\alpha_{j1} - c_j) - (\beta_j\beta_k - \gamma_j\gamma_k)h^*_{j1} - \gamma_j\big(\alpha_k - (l_k + \phi_k)\big)}{(\beta_j\beta_k - \gamma_j\gamma_k)\Delta h_{j1}}, \tag{1.11}$$

imposing that $s_j \in (0,1)$ lies in the defined area. In this context, the behaviour of type j homeowners does not at all depend on the actions taken by type k homeowners. Besides, the solution collapses to the one of homogeneous housing for $\gamma_j = 0$.

Next, we examine the more complex case, in which homeowners maximise their short-term profits simultaneously, taking into account their competitor's reaction. This setting applies, if both housing segments suffer an overhang, $\Delta h_{j1} \geq 0$ and $\Delta h_{k1} \geq 0$. The individual optimization problem of a type j homeowner reads:

$$\begin{aligned}\arg\max_{s_j}\ & \pi^i_{j1} = \big(\alpha_{j1} - \beta_j x_{j1} - \gamma_j x_{k1} - c_j\big)\Delta h_{j1} s^i_j,\\ \text{s.t. }\ & s_j \in (0,1),\\ & p_{j2} > 0.\end{aligned}$$

Short-term home sales $x_{j1} = h^*_{j1} + \Delta h_{j1}(s^i_j + s^{-i}_j)$ and $x_{k1} = h^*_{k1} + \Delta h_{k1}(s^i_k + s^{-i}_k)$ depend on the sales decision of the respective type of homeowner. The two players have symmetric maximization problems, because they move at the same time and also share symmetric inverse demand functions and marginal costs. Therefore, all the calculations analogously hold for type $k \neq j$ homeowners. The partial derivative with respect to s^i_j specifies a homeowner's reaction function:

$$s^i_j = \frac{1}{2\beta_j \Delta h_{j1}}\big((l_j + \phi_j) - \beta_j \Delta h_{j1} s^{-i}_j - \gamma_j \Delta h_{k1} s_k - c_j\big), \tag{1.12}$$

since $\alpha_{j1} - \beta_j h^*_{j1} - \gamma_j h^*_{k1} = l_j + \phi_j$. Summing for all n_j individuals, $\sum_i^{n_j} s^i_j = s_j$ and $\sum_i^{n_j} s^{-i}_j = s_j(n_j - 1)$, and solving for s_j further gives:

$$s_j = \frac{n_j}{(n_j+1)} \frac{(l_j + \phi_j) - \gamma_j \Delta h_{k1} s_k - c_j}{\beta_j \Delta h_{j1}}. \tag{1.13}$$

As one can see, s_j still depends on the competing homeowner's share of offered oversupply. We therefore derive s_k based on symmetry considerations, $s_k = \frac{n_k}{(n_k+1)} \frac{(l_k+\phi_k) - \gamma_k \Delta h_{j1} s_j - c_k}{\beta_k \Delta h_{k1}}$, and substitute the resultant expression into Equation 1.13 to determine the optimal response of type j homeowners:

$$s^*_j = \frac{n_j}{\Delta h_{j1}} \frac{(n_k+1)\beta_k\big((l_j+\phi_j) - c_j\big) - n_k \gamma_j \big((l_k + \phi_k) - c_k\big)}{(n_j+1)(n_k+1)\beta_j\beta_k - n_j n_k \gamma_j \gamma_k}, \tag{1.14}$$

imposing that $s_j \in (0,1)$ lies in the defined area. The behaviour of type j homeowners depends on the the opportunity costs of competing homeowners, c_k. Accordingly, the future price trajectory of the competing housing segment, p_{k2}, indirectly affects the sales decision of type j homeowners today. Besides, the solution nests the one of homogeneous housing for $\gamma_j = 0$.

On these grounds, we reassemble the optimal sales strategy of homeowners in two steps.

In line with Figure 1.5, we first establish whether or not the housing segment j suffers an oversupply. If not, $\Delta h_{j1} < 0$, type j homeowners meet the residual housing demand unsatisfied by their competitors, $x_{j1} = \big(\alpha_{j1} - \gamma_j x_{k1} - (l_j + \phi_j)\big)/\beta_j$. Otherwise, $\Delta h_{j1} \geq 0$, short-term home sales in this segment, $h^*_{j1} + \Delta h_{j1} s^*_j$, depend on the willingness s^*_j of the incumbent homeowners to sell immediately:

$$x^*_{j1} = \begin{cases} \frac{\alpha_{j1} - \gamma_j x_{k1}(s_k) - (1+\phi_j)}{\beta_j}, & \text{if } \Delta h_{j1} < 0 \quad , \\ \\ h^*_{j1} + \Delta h_{j1} s^*_j, & \text{if } \Delta h_{j1} \geq 0 \quad . \end{cases} \tag{1.15}$$

Provided that type j homeowners face an oversupply, $\Delta h_{j1} \geq 0$, they need to determine the optimal share of offered oversupply, s^*_j, in the second step. The type j homeowners only decide strategically, if houses have an economic value even after retarding a sale, $p_{j2} > 0$. Otherwise, $p_{j2} = 0$, they sell immediately anyway, $s_j = 1$. However, if the housing downturn supports a positive economic value, $p_{j2} > 0$, homeowners need to account for how the downturn distributes bargaining power across the two competing housing segments. They enjoy a first-mover advantage, if the competing segment lacks houses, $\Delta h_{k1} < 0$. On the other side, type j and k homeowners decide simultaneously, if both segments experience excess supply. This leads to:

$$s^*_j = \begin{cases} \frac{n_j}{(n_j+1)} \frac{\beta_k(\alpha_{j1} - c_j) - (\beta_j\beta_k - \gamma_j\gamma_k)h^*_{j1} - \gamma_j(\alpha_{k1} - (l_k + \phi_k))}{(\beta_j\beta_k - \gamma_j\gamma_k)\Delta h_{j1}}, & \text{if } p_{j2} > 0, \text{ and } \\ & \Delta h_{j1} \geq 0,\ \Delta h_{k1} < 0, \\ \\ \frac{n_j}{\Delta h_{j1}} \frac{(n_k+1)\beta_k((l_j+\phi_j) - c_j) - n_k\gamma_j((l_k+\phi_k) - c_k)}{(n_j+1)(n_k+1)\beta_j\beta_k - n_j n_k \gamma_j \gamma_k}, & \text{if } p_{j2} > 0, \text{ and } \\ & \Delta h_{j1} \geq 0, \Delta h_{k1} \geq 0, \\ \\ 1, & \text{if } p_{j2} = 0, \end{cases} \tag{1.16}$$

as long as $s^*_j \in (0,1)$ is satisfied.

In summary, homeowners are confronted with a multi-stage decision problem. The structure of the decision problem depends on the housing market conditions. Sometimes homeowners enjoy a first-mover advantage or a simultaneous decision problem, sometimes they simply serve the residual housing demand or do not decide strategically at all. In the case that homeowners consider to strategically postpone a sale during downturns, their willingness to sell immediately declines in the size of excess supply, Δh_{j1}, and in the opportunity costs, c_j. At the same time, the opportunity costs rise in the oversupply, while the cross-segment competition diffusely interferes with the optimal share of offered oversupply in the numerator and the denominator. Therefore, any definite solution to the outlined multi-stage decision problem rests upon simulations.

1.4 Simulation Analysis

We now explore in depth how different parameter and variable values affect the optimal sales decision of homeowners during downturns. This is necessary for two reasons. First, the supposed market structure frames the final outcome *a priori* because it defines the direction and extent of cross-segment dependence. Hence, understanding how variations in the parameterization work out is indispensable. Second, the variables considered form potential policy instruments as they derive from economic and political processes outside the housing market. This might open up new, though possibly indirect, ways of intervening in struggling housing markets.

Some words of caution are in place before continuing with the simulations. Please remember that in the model the initial demand shock is supposed to be permanent. This is of course overly simplistic as compared to a temporary demand shock. It also implies a tendency to overestimate the extent of the simulated downturn and, hence, its impact on the behaviour of homeowners and house prices. However, given the multitudes of rigidities in housing markets, e.g. demand remains subdued even eight years after the US Housing Crisis has started, a permanent demand shock appears to be a farily reasonable approximation.

In order to characterise the sales decision of homeowners subsequent to declining housing demand, we investigate four different properties. The first property is the aggregate share of withdrawn oversupply, $ws_j = 1 - s_j$, $ws_j \in (0, 1)$. This reports the number of homeowners who should optimally postpone a sale in the immediate short term and the extent to which they actually exercise their market power. The next property considered is the discounting of the immediate short-run price and the Bertrand price, i.e. when no strategic decision making is possible ($s_j = 0$), versus the initial market price, $d_{j1} = p_{j1}/p_{j0} - 1$, and $d_j^B = p_j^B/p_{j0} - 1$. The third property is the logarithmic supply elasticity of prices, $\eta_{j1} = \log\big((p_{j1} - p_{j0})/(x_{j1} - x_{j0}) \times x_{j0}/p_{j0}\big)$, which summarises whether the immediate short-term adjustment is primarily shouldered through the house prices or the home sales. A value of the supply elasticity above (below) zero suggests that prices (home sales) bear the bulk of the immediate short-run adjustment. This form of market clearing corresponds to the "quantity clearing mechanism" ("price clearing mechanism") defined by Case and Quigley (2008). The last property is the housing inventory expressed in terms of home sales, $hi_j = h_{j0}/x_{j1} - 1$. It portrays how a strongly hidden supply skews home sales during a downturn.

For ease of illustration, we further concentrate on demand shocks, ε, of up to 0.5. Not only do shocks of that size hardly ever occur in reality, but also there are no remarkable dynamics beyond this threshold. Moreover, some inputs are generally used for model calibration purposes: the depreciation rate, δ, equals 2.0% (net of maintenance) in accordance with a recent empirical study (Harding et al., 2007). The long-run risk-free rate, r, is set to 5.0% to be reasonably close to the 5.3% historical average of the US Federal Funds Rate between 1955 and 2012. The assumed ten-year maturity of mortgages, T, mimics the typical loan arrangements (before refinancing). All the other inputs are discussed in the relevant context below. A summary of all the applied parameterizations is given in Table A.1 in the appendix.

The simulation exercise indicates that homeowners typically have a strong incentive to postpone a sale in housing downturns. This optimal sales strategy, however, fails to deliver a reasonable explanation for the spillovers observed in the "Subprime Crisis". More precisely, homeowners tend to postpone a sale rather than realizing an immediate loss, consistent with survey evidence (cf. Case and Shiller, 1988; Case et al., 2003; Case et al., 2012). Home sales accordingly carry the majority of the immediate short-term adjustment. House prices are therefore rather sticky. Serious spillovers transpire, only if the demand for one segment is not sustainable in the long-term. However, this condition appears unfit to describe even the recent "Subprime Crisis". Thus, we need to refine the model assumptions further in the subsequent section, where appropriate. Further investigation of the potential policy instruments shows that fiscal stimuli, monetary policy and urban policy might strengthen the incentive of homeowners to delay their sale. This sales strategy indirectly stabilises tumbling housing markets.

1.4.1 Homogeneous Housing Market

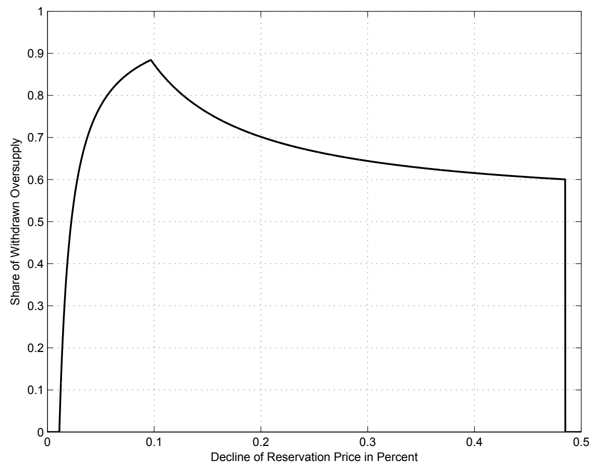
The homogeneous housing market serves as a starting point due to its simplicity. The model specific parameters are $\alpha = 2$, $\beta = 1$, and $\phi = 3.0\%$. In this way, we ascertain that house price increases translate into similar reductions in home sales. Besides, the reservation price equals roughly twice the size of the marginal costs.

The simulations in Figure 1.6 portray the optimal sales strategy of homeowners and its implications for house prices. Homeowners start to postpone their sales strategically if the negative demand shock exceeds 1.2%. The peak of deliberate withdrawals is reached for an exogenous shock of 9.0%. At this stage, homeowners artificially shorten the existing oversupply by roughly 88.0%. For higher levels of oversupply they withdraw increasingly less because a late sale is also less favourable. Nonetheless, homeowners remove at least 60% of the housing surplus for as long as their property holds a positive long-term value. In this way, homeowners effectively smooth the available excess supply for sale during housing downturns. The resulting short-term price discount is therefore less depressed than in the absence of strategic withdrawals.

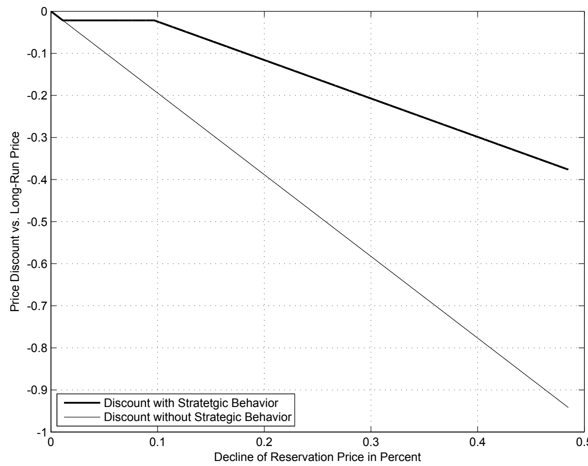
Furthermore, the optimal sales strategy of homeowners implies that house prices remain rather sticky leaving most of the adjustment to home sales. Indeed, the predominantly negative sign of the supply elasticity indicates that home sales bear the bulk of the immediate short-term adjustment in most scenarios ("quantity clearing mechanism"). Only for demand decreases below 2.0% does the relation reverse ("price clearing mechanism"). The supply elasticity reaches its minimum precisely when the share of strategically postponed sales peaks. At this point, the contraction in home sales is more than eight times the drop in house prices. Besides, the build-up of the housing inventory necessary to accommodate withdrawals is economically significant. For instance, decreases in the reservation price of 5.0% already yield a double-digit build-up of the housing inventory. Hence, the model predicts sticky house prices facilitated by a corresponding reduction in home sales and respective growth in the housing inventory.

1.4.2 Heterogeneous Housing Market

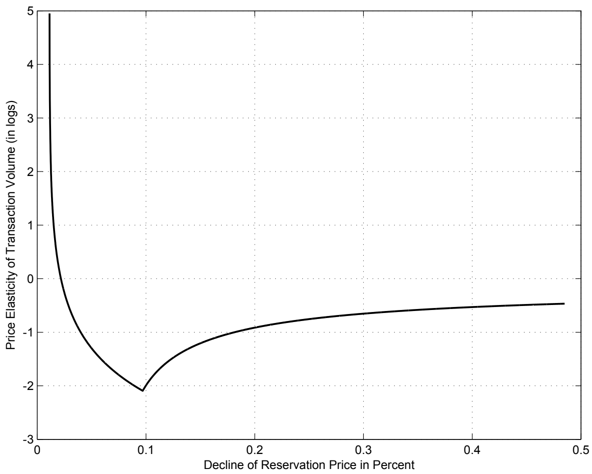
Next, we repeat the simulation analysis for the heterogeneous model. To keep matters simple, we apply all of the previous parameter and variable values symmetrically to both



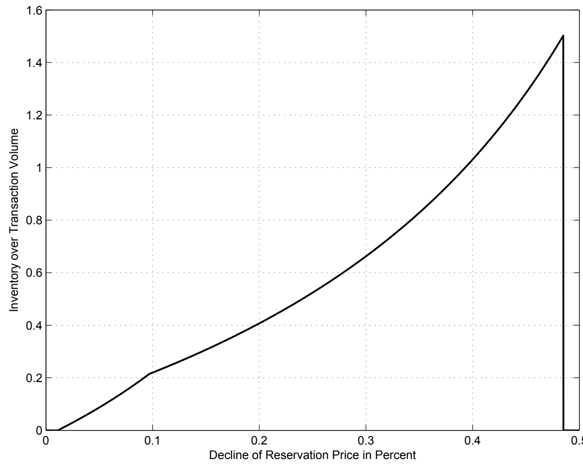
(a) Share of withdrawn oversupply.



(b) Price discount vs. long-run house price.



(c) Price elasticity of home sales.

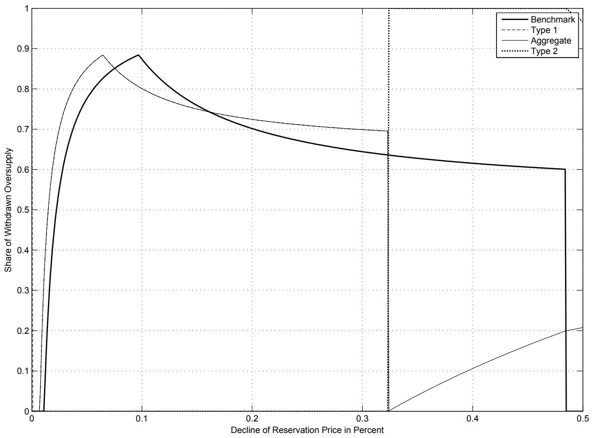


(d) Inventory over Home Sales.

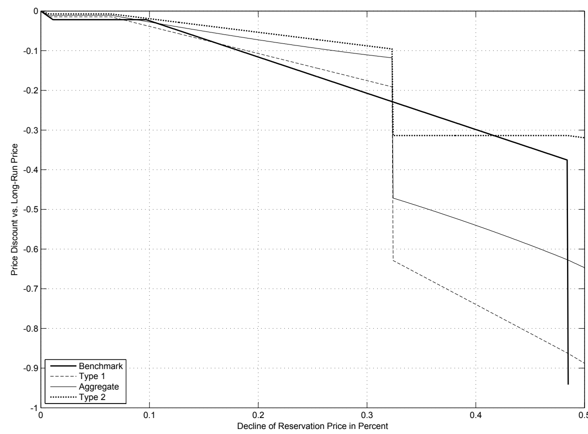
Figure 1.6: Homogeneous housing market. This figure characterises the optimal sales decision of homeowners in a homogeneous market. Sections (a) to (d) exhibit different properties of the model: the share of withdrawn oversupply, price discounts, price elasticity and housing inventory. The respective properties are depicted on the vertical axis. The percentage decline in the reservation price is on the horizontal axis. For details on the parameterization please confer to Table A.1 in the appendix.

segments. The newly introduced spillovers are uniformly set to $\gamma_j = 0.5$, so they are economically relevant, but do not dominate the outcome. With a co-movement of $\rho = 0.5$, the exogenous shock primarily hits type 1. Under these conditions, only type 1 houses face an initial oversupply, because the substitution effect neutralises the correlated decline in demand of type 2 housing. This setting constitutes the standard calibration.

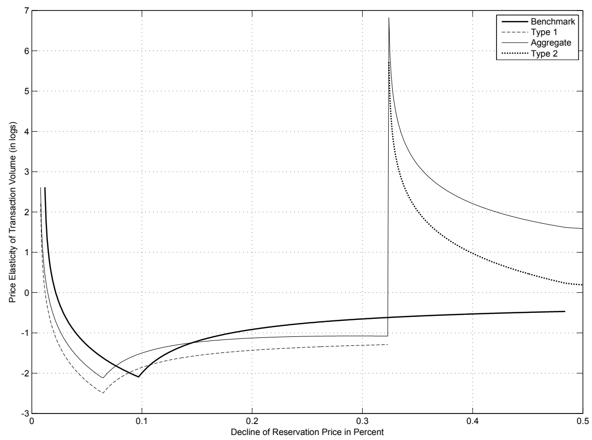
The simulation results exhibited in Figure 1.7 characterise the optimal sales strategy of homeowners in the two segments and on an aggregated level. The homogeneous model results are also included as a natural benchmark. The exercise reveals profound disparities regarding how the two types of homeowners respond to a downturn. Type 1 homeowners show an optimal sales strategy that is qualitatively similar to the homogeneous case. The extent to which they postpone a sale strategically is initially more pronounced. However, type 1 homeowners also stop deciding strategically at a lower level of oversupply (33.0% vs. 48.5%) since their market segment is already failing. By contrast, type 2 homeowners do not postpone a sale until then. However, since at least 95.0% of their oversupply should be withdrawn, they have an optimally higher motivation to delay. Nonetheless, the sales strategy of type 1 homeowners dominates the share of withdrawn oversupply on an aggregated level.



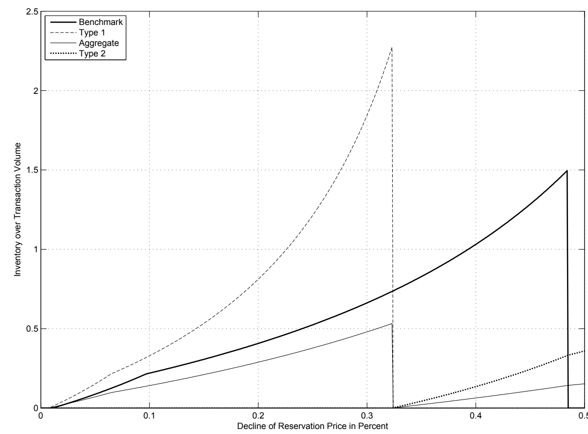
(a) Share of withdrawn oversupply.



(b) Price discount vs. long-run house price.



(c) Price elasticity of home sales.



(d) Inventory over home sales.

Figure 1.7: Heterogeneous housing market. This figure characterises the optimal sales decision of homeowners in a heterogeneous market. Sections (a) to (d) exhibit different properties of the model: the share of withdrawn oversupply, price discounts, price elasticity and housing inventory. The respective properties are depicted on the vertical axis. The percentage decline in the reservation price is on the horizontal axis. For details on the parameterization please confer to Table A.1 in the appendix.

These findings suggest that cross-segment competition plays a critical role in the optimal sales decision of homeowners. The reason is that it causes a substitution effect, which rises with the intensity of cross-segment competition. The substitution effect mitigates the size of the aggregate oversupply. This in turn provides homeowners with greater discretion in exercising their market power. Thus, cross-segment competition to some extent supports the incentive of homeowners to postpone a sale. On the downside, fierce cross-segment competition reduces the market depth. Therefore, the capacity of the housing market to absorb oversupply decreases and the threshold at which a market segment dissolves falls. This compromises the strategic sales decision of homeowners. Hence, cross-segment competition bolsters the exercise of bargaining power by homeowners for low to moderate excess supply, but harms it in the presence of a substantial overhang.

House prices respond to cross-segment competition accordingly. The price discount of type 1 houses is consistently larger than that of type 2 houses. The aggregated transactions-based price discount is skewed towards type 2 housing, since the withdrawals of type 1 homeowners undermine their weight in the aggregation. More importantly, the prices in both segments are higher than the homogeneous benchmark, unless the type 1 housing segment dissolves, but then the collapse of the worst-affected segment instantly spills over, as both segments witness a considerable drop in the short-term price below the homogeneous benchmark. Hence, house prices might suddenly plummet under extreme conditions provided that the excess supply grows sufficiently large.

Cross-segment competition also interferes with the aggregate supply elasticity and housing inventory. Prior to a collapse of the market for type 1 housing, the aggregate elasticity not only strongly resembles that of this segment, but is also smaller than for the homogeneous benchmark. However, once the market for type 1 housing dissolves, the aggregate elasticity is more closely tied to type 2 housing and higher than that for the homogeneous benchmark. The supply elasticity further jumps to positive values following the segment's demise. Thus, discontinuities in the share of withdrawn oversupply turn the "quantity clearing mechanism" into a "price clearing mechanism". In addition, the housing inventory reveals that the magnitude of aggregate supply shortages is generally lower than in the homogeneous case. This is astonishing insofar as the implied price discounts are lower in the heterogeneous setting after all. Thus, the benefits resulting from cross-segment competition also affect the extent of housing inventory formation.

In summary, a heterogeneous housing market resists small to moderate demand declines, but is prone to sudden and intense price drops for large decreases in the housing demand. First, the incentive for homeowners to withdraw from the market is more pronounced but collapses at lower levels of oversupply than in a homogeneous context. Second, the aggregate house price experiences a smaller discount than in the benchmark scenario, unless one segment dissolves. Third, in case that a segment dissolves, the housing market clears through a "quantity clearing mechanism" rather than a "price clearing mechanism". This illustrates that house price spillovers are the result of a collapse of strategic decision making in one segment and are spread via cross-segment competition. Hence, a segmented housing market tends to be more stable for small to moderate levels of oversupply, but at the cost of increased vulnerability for high levels.

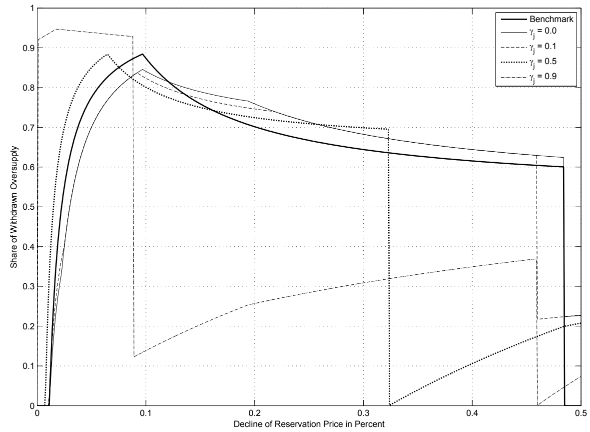
1.4.3 Cross-Segment Competition and Shock Co-Movement

In order to explore how the newly introduced factors—quantity spillovers and shock correlation—influence the short-term market allocation and accordingly the fragility of housing markets, we repeat the simulation for varying levels of γ_j and ρ. Both times, the respective parameters are *ceteris paribus* set to 0.1, 0.5 and 0.9. We summarise the simulation results in Figure 1.8 by means of strategic interaction and price discounts.[14]

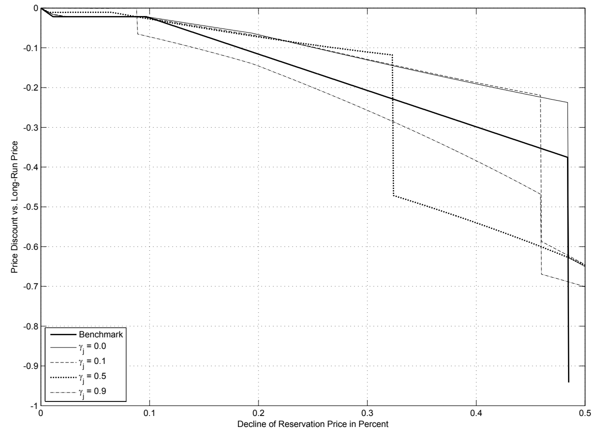
We first investigate the impact of different quantity spillovers. In accordance with our earlier simulation results, higher cross-segment competition promotes house price stability for low and moderate oversupply, but it increases the fragility of house prices faced with a large overhang, too. The reason is that cross-segment competition alleviates the aggregate oversupply at the cost of lower market depth. The latter increases the sensitivity of a homeowner's sales strategy to the size of excess supply. The house prices behave accordingly. They are higher than in the homogeneous setting as long as homeowners decide strategically. However, once one market segment breaks down, the price discount is far more elevated in the presence of high cross-segment competition. Hence, from a risk perspective, quantity spillovers contribute to the fragility of house prices in times of substantial downturns.

Varying levels of shock co-movement affect the sales decision of homeowners in three ways. First, the lower the shock correlation, the higher the incentive for homeowners to retard a sale unless no market segment collapses. This is because the shock correlation erodes the substitution effect. However, the substitution effect provides homeowners with a greater discretion in exercising market power. Thus, a smaller co-movement translates

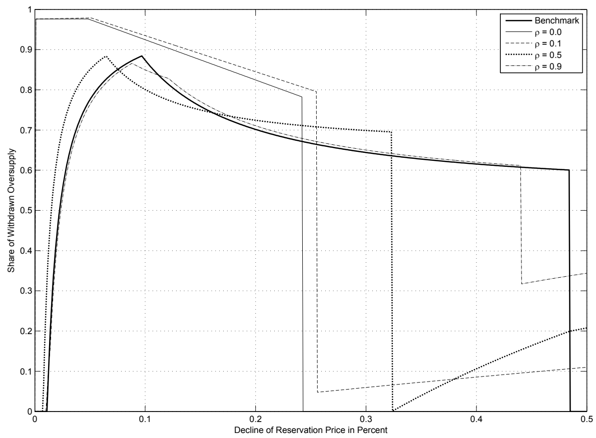
[14] The simulation results regarding the supply elasticity and housing inventory are included in Figures A.1 and A.2 in the appendix.



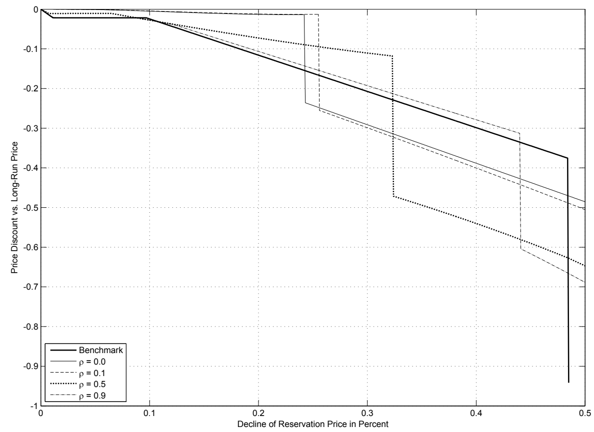
(a) Cross-segment competition: Share of withdrawn oversupply.



(b) Cross-segment competition: Price discount vs. long-run house price.



(c) Shock co-movement: Share of withdrawn oversupply.



(d) Shock co-movement: Price discount vs. long-run house price.

Figure 1.8: Cross-segment competition and shock co-movement. This figure illustrates how the optimal sales decision of homeowners responds to changes in cross-segment competition and shock co-movement by means of the share of withdrawn oversupply and the associated price discounts. The respective properties are depicted on the vertical axis. The percentage decline in the reservation price is on the horizontal axis. For details on the parameterization please confer to Table A.1 in the appendix.

into a higher incentive to postpone a sale. Second, for a small shock co-movement, the incentive to time a sale takes a nosedive at lower levels of oversupply. Since a low shock correlation bolsters the substitution effect, it also abates the market depth, but a thin market is less capable of absorbing oversupply. It dissolves more easily. Thus, a low shock correlation reduces the threshold at which homeowners lose any interest in strategically keeping a house away from the market. Third, the higher the shock co-movement, the more the strategic sales decision of homeowners resembles the homogeneous benchmark. This is due to the fact that the otherwise symmetric market segments are increasingly affected in the same way. Again, the house prices act accordingly. As long as homeowners behave strategically, the discounts are lower. However, the aggregate market prices fall noticeably short of their homogeneous benchmark, once this condition is violated in (at least) one segment. Hence, a low shock co-movement features rather stable house prices in small to moderate oversupply scenarios, but material price drops when the overhang is substantial.

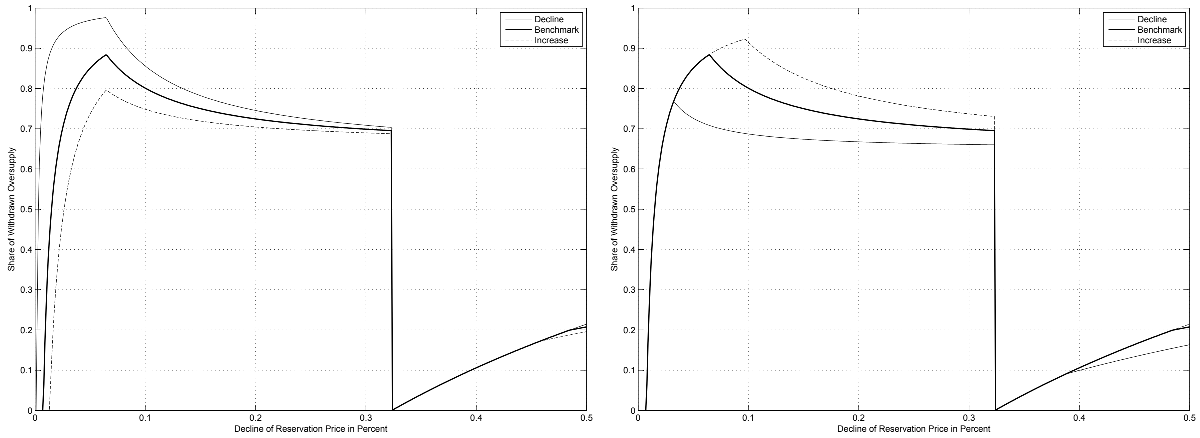
In a nutshell, both cross-segment competition and shock co-movement considerably interfere with the stability of the housing market. It turns out that a heterogeneous housing market is more stable than its homogeneous equivalent as long as strategic decision making is intact. On the other side, the threshold at which this precondition is no longer satisfied rises with the two factors. The reason is that both factors alleviate the aggregate oversupply at the cost of lower market depth, but the latter increases the sensitivity of a homeowner's sales strategy to the size of the excess supply. After all, cross-segment competition and shock co-movement influence how a given level of oversupply affects the ultimate sales decision of homeowners and thus the entire housing market.

1.4.4 Influencing Seller Behaviour

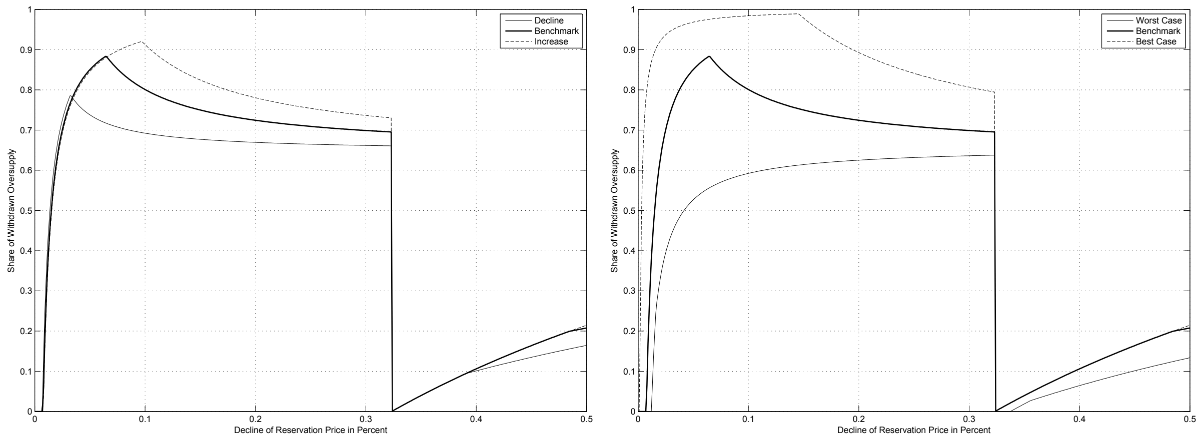
Now, we turn to three key exogenous variables, the adjustment of which might be influenced by policy makers: the interest rate, r, the time to maturity, T, and the depreciation rate, δ_j. We explore how policy interventions could diminish the negative consequences of market downturns for house prices through influencing the sales decision of homeowners.

For the analysis we concentrate on the aggregate share of withdrawn oversupply (cf. Figure 1.9. We start by examining the impact of monetary policy. Subsequent to a cut (mark-up) in the interest rate to $r = 1.0\%$ ($r = 9.0\%$) more (less) homeowners *ceteris paribus* retreat from the market. This is because a lower (higher) interest rate raises (decreases) the opportunity costs of staying in the market. Selling later (immediately) therefore becomes more attractive. Besides, the effect is most pronounced for a rather small oversupply ($\varepsilon \leq 7.5\%$). However, even lower interest rates cannot prevent homeowners from ceasing to time their sale strategically at some point. Besides, the threshold at which the strategic sales decision making of homeowners takes a nosedive remains unchanged. After all, though, monetary policy constitutes one way in which central banks might intervene in struggling housing markets.

Two other fields of interest are urban policy and financial stimuli. Urban policy might



(a) Monetary policy: Adjusting interest rate r. **(b) Urban policy:** Adjusting replacement rate δ_j.



(c) Fiscal stimuli: Adjusting maturity T. **(d) Policy scenarios.**

Figure 1.9: Policy interventions. This figure characterises the optimal sales decision of homeowners in a heterogeneous market under policy interventions. The homogeneous market allocation serves as a benchmark. The percentage decline in the reservation price is on the horizontal axis and the share of withdrawn housing units on the vertical axis. Sections (a) to (c) delineate the effect of policy interventions by instrument (r, δ, T). Section (d) defines concerted policy interventions. For details on the parameterization please confer to Table A.1 in the appendix.

affect the depreciation rate, δ_j, by encouraging either the formation or the demolition of the housing stock. Financial stimuli could further incentivise mortgage creditors and debtors to modify the time to maturity, T, of existing mortgages where appropriate. Changing the depreciation rate, δ_j, or the time to maturity, T, has a very similar effect on the sales decision of homeowners. In both cases, a reduction (increase) in the respective factor by half causes strategic interaction to peak at lower (higher) levels of oversupply. Until then, the trajectory of optimal homeowner behaviour evolves almost identically to the baseline case. This results from the fact that both variables primarily govern the same model dynamic: total depreciation $T\delta_j h_{j1}$.[15] As before, the two factors have no influence on the threshold at which a temporary breakdown of strategic behaviour occurs.

[15] T further affects the capital formation, $I(T)$, and the discount factor, $1/(1+r)^T$.

Therefore, urban policy and financial stimuli may indirectly stabilise house prices in the immediate short term.

In order to explore the limits of policy interventions in stabilizing a heterogeneous housing market during downturns, we define a best-case ($r = 1.0\%, \delta_j = 3.0\%, T = 15$) and a worst-case scenario ($r = 9.0\%, \delta_j = 1.0\%, T = 5$). Under the best-case scenario, the joint effort of monetary policy, urban policy and financial stimuli raises both the extent and the persistence of shortened oversupply. In particular, prior to a nosedive in strategic behaviour far more homeowners avoid selling immediately. Moreover, the peak of strategically postponed sales shifts outwards. Under the worst case scenario both conclusions reverse. Hence, concerted policy interventions are capable of significantly strengthening the incentive of homeowners to retard a sale strategically during market downturns. This indirectly stabilises house prices in both market segments.

1.5 Revisiting the 2006-09 US Housing Market Crash

This section examines the collapse of the US housing market between 2006 and 2009, taking into account some of the key market features at the time, such as the division into a "subprime" and a "prime" segment, high leverage, and non-recourse financing. Under the recalibrated model, destructive spillovers occur when homeowners lose the incentive to postpone a sale, because they default. Besides, should banks see a need to allocate capital to foreclosed homes first non-distressed home sales might also be crowded out. In both cases, house prices are forced down.

1.5.1 Non-Recourse Financing and Credit Quality

The US housing market is made up of two segments. By 2006, the "subprime" segment accounted for roughly one-fifth of the market and the "prime" segment for the remainder.[16] The subprime segment is defined by the typically lower creditworthiness of homeowners compared with their prime counterparts. For the same reason, subprime houses are typically smaller, while the mortgage rates are more expensive (abstracting from so-called

[16] According to Frame et al. (2008), the entire US residential mortgage market had an estimated value of USD 10.0 tn at year-end 2007. The subprime segment accounted for USD 1.2 tn in first-lien mortgages and another USD 1.1 tn in second-lien mortgages.

teaser rates, which defer the interest burden for some time).[17] Interestingly, despite the lower credit quality, subprime homeowners often obtain higher leverage since they require a smaller initial downpayment. For instance, in 2006, the median (average) loan-to-value ratios of newly issued (existing) subprime and prime mortgages were about 0.93 (0.85) and 0.80 (0.73) (cf. Frame et al., 2008; Gao and Li, 2013; Palmer, 2013).

Another missing element in our analysis is the possibility of strategic defaults of homeowners. In accordance with US bankruptcy, law retail mortgages are typically non-recourse Harris (2010). This practice prevents creditors from seizing the remaining property of debtors in the case of default. Thus, homeowners possess an option to stop serving their mortgage once the future loan payments surpass the expected proceeds. Let a homeowner's outstanding obligation at maturity equal $ltv_j p_{j0}(1+r)^T$, where ltv_j denotes the loan-to-value ratio (LTV). Her capitalised proceeds are $p_{j2}\big(1+\omega I(T-1)\big)+\omega p_{j0}(1+r)^T$. Thus, if the following participation condition is violated,

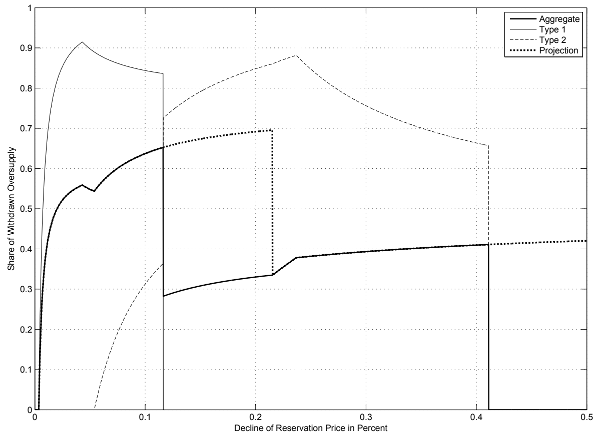
$$ltv_j p_{j0}(1+r)^T \geq p_{j2}\big(1+\omega I(T-1)\big)+\omega p_{j0}(1+r)^T,$$

all respective homeowners default on their mortgages.[18]

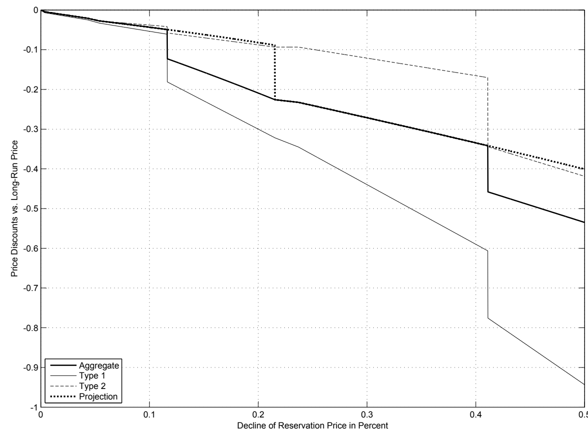
Taking these characteristics into account we re-calibrate the heterogeneous model. Type 1 housing is referred to as "subprime" and type 2 housing as "prime". The corresponding loan sizes are $l_1 = 1$ and $l_2 = 2$ to reflect the differentials in credit quality. The leverage that subprime and prime homeowners obtain by borrowing against collateral closely matches that prior to the crisis, $ltv_1 = 0.9$ and $ltv_2 = 0.8$. The agio paid for the service of financial intermediation equals $\phi_j = 0.06$ in both cases. In this way, the marginal costs of (high risk) subprime homeowners in terms of house size are still higher than those for (low-risk) prime homeowners: $1.06 = c_1/v_1 > c_2/v_2 = 1.03$. We set the reservation price of subprime homeowners to $\alpha_1 = 2.0$ and choose that of prime homeowners so that the subprime segment accounts for roughly 20.0% of the housing market. The remaining parameters and variables remain unaltered: $\beta_j = 1$, $\gamma_j = 0.5$, $\rho = 0.5$, $\delta_j = 2\%$, $T = 10$, and $r = 5\%$.

17 For details, see Figures 1 and 12 in Chomsisengphet and Pennington-Cross (2006).

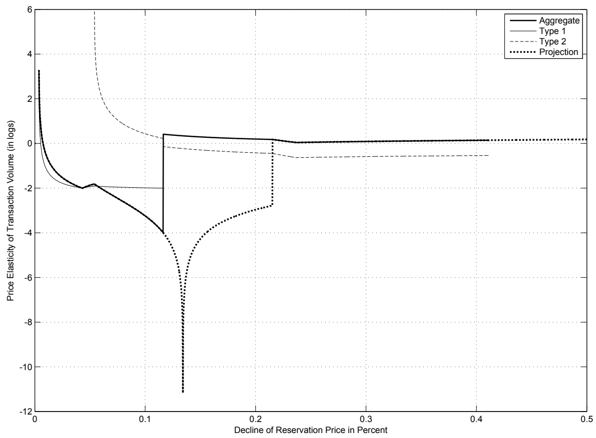
18 For simplicity, we abstract from the fact that in reality a violation of this condition, often referred to as negative equity, is a necessary but not a sufficient condition for borrower default as Foote et al. (2008) point out. Besides, Harris (2010) explained that roughly 20.0% or 588,000 of all foreclosures in 2008 were due to strategic defaults.



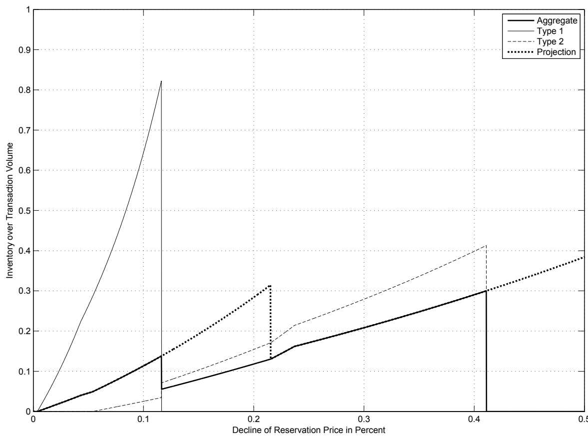
(a) Share of withdrawn oversupply.



(b) Price discount vs. long-run house price.



(c) Price elasticity of home sales.



(d) Inventory over home sales.

Figure 1.10: Foreclosures and house prices. This figure characterises the optimal sales decision of homeowners in a heterogeneous framework customised to the specifics of the US housing market. Sections (a) to (d) exhibit different properties of the model: the share of withdrawn oversupply, price discounts, price elasticity and housing inventory. The respective properties are depicted on the vertical axis. The percentage decline in the reservation price is on the horizontal axis. For details on the parameterization please confer to Table A.1 in the appendix.

The introduction of a participation constraint considerably undermines the incentive of homeowners to postpone a sale strategically compared with a projection abstracting from deliberate defaults. While their efforts to delay home sales are undisturbed for low levels of overhang, the participation constraint of subprime homeowners soon becomes binding. They consequently default. Despite a simultaneous increase in strategic withdrawals by prime homeowners, the aggregate share of the withdrawn oversupply is nearly halved. In the same way deliberate defaults prematurely compromise the strategic rationale of prime homeowners once their participation constraint is violated for high levels of oversupply. Thus, as soon as the participation constraints of homeowners are effectively binding, subprime and prime homes may suddenly flood the housing market.

The house prices react accordingly. They remain relatively stable unless a participation constraint is no longer satisfied and a sell-off occurs. For instance, in the case that moderate oversupply unleashes a sell-off of subprime homes, the price drop in this segment is particularly pronounced and also dominates the aggregate house price, notwithstanding its small market share. This is because exclusively prime homeowners postpone a sale, whereas all subprime houses are thrown onto the market. Moreover, in the case that a large oversupply even triggers a sell-off of prime houses, the quantity shock directly translates into another plunge in house prices. This time, the aggregate house price decline is dominated by the prime segment. Hence, house prices are vulnerable to sell-offs as a result of deliberate defaults by either of the two types of homeowners.

A look at the supply elasticity further shows that strategic defaults turn the traditional "quantity clearing mechanism" into a "price clearing mechanism" (cf. Case, 2008). On one side, the aggregate supply elasticity abruptly turns positive after the participation condition is violated. On the other side, the projected elasticity ignoring deliberate defaults remains negative, even for more sluggish demand. Hence, without the default option provided by the US bankruptcy law, housing markets would remain quantity-driven except for large excess supply. Only after deliberate defaults prompt a sell-off in the subprime segment does the housing market as a whole clear through prices. Even a far above-average formation of housing inventory, shouldered by prime homeowners cannot reverse this. The way in which a market clears in the immediate short term therefore strongly depends on the actual design of the bankruptcy law and mortgage contracts.

In summary, the re-calibrated heterogeneous housing market model portrays fairly well several key characteristics of the 2006-09 housing market crash. First, the decline in house prices accelerated over time (Financial Times, 2008). This observation is compatible with the gradually declining demand for housing in the model—at first slowly, then increasingly pronounced. At some point, the sell-offs predicted by the simulation for moderate and large oversupply speed up the price drops. Second, the house price declines were closely intertwined with the rising foreclosure rates, which concentrated in the subprime segment (cf. Campbell et al., 2011; Frame et al., 2008; Mian et al., 2014). From a model perspective, this relates to strategic defaults. Once the oversupply becomes sufficiently large, future house prices no longer cover the outstanding obligations of homeowners. In anticipation of a loss, they exercise their non-recourse default option. As a result, house prices slump precisely when foreclosure rates jump up. Moreover, foreclosures concentrate in the subprime segment because its above-average leverage makes the participation constraint of homeowners particularly binding. Thus, the subprime segment is more sensitive to oversupply. Third, home sales, which became increasingly dominated by distressed sales in the subprime segment, slumped, while the housing inventory surged (CoreLogic, 2010). The model draws the same conclusion: while prime homeowners prefer to keep out of the market and wait for higher future sales prices, subprime homes in foreclosure trade on the market (Case, 2008). Hence, when accounting for the strategic defaults of homeowners, their strategic sales decision establishes a link between oversupply, house price declines, mortgage defaults and the rising housing inventory, which is consistent with the recent US housing crash.

1.5.2 Mortgage Losses and House Prices

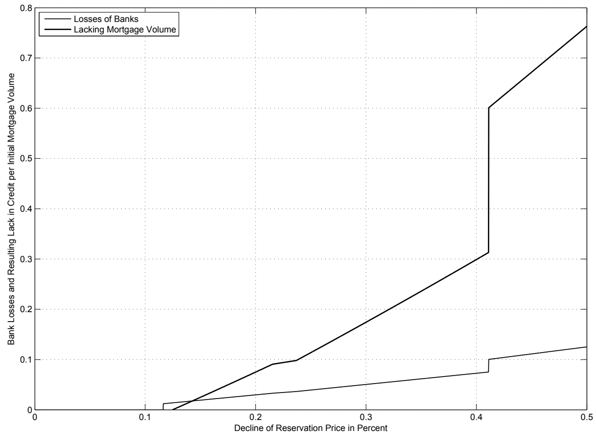
Finally, we investigate how banks sustaining mortgage losses interfere with house prices. The empirical evidence suggests that banks with branches in several regions shifted scarce lending capacity to those branches that experienced the most devastating mortgage losses during the US housing market crash Berrospide et al. (2013). In this way, they tried to balance the burden of mortgage losses. The subsequent question is how this pecking order, which favours distressed home sales, affects house prices?

For this purpose, we conduct another simulation. In order to reflect reality as closely as possible, we refine some further assumptions. First, the banking sector pursues a lending policy that prefers distressed home sales (cf. Berrospide et al., 2013). Second, the banking sector is leveraged. In fact, US commercial banks held about 10.0% of their assets in equity prior to the crisis.[19] Third, the banking sector maintains its leverage. Otherwise, bank regulators would intervene in troubled institutions. The Federal Deposit Insurance Company alone assisted 181 US commercial banks between 2006 and 2009. [20] Moreover, the exercise proceeds as follows: initially, the immediate short-term prices are computed for each segment. Next, we determine the resulting losses per segment. Losses

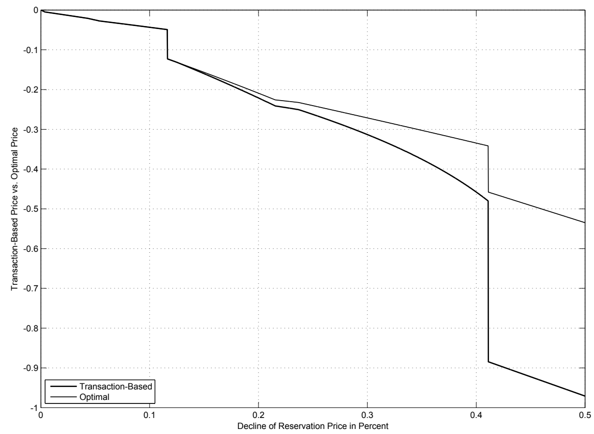
[19] According to the Federal Deposit Insurance Company's SDI database, US commercial banks had total assets of USD 10.1bn and held total equity capital of USD 1.0bn as of 31 December 2006: http://www2.fdic.gov/sdi/main.asp.

[20] The data stem from the Federal Deposit Insurance Company's "Failures and Assistance Transactions" database: http://www2.fdic.gov/hsob/HSOBSummaryRpt.asp?BegYear=2007&EndYear=2009&State=2&Header=0.

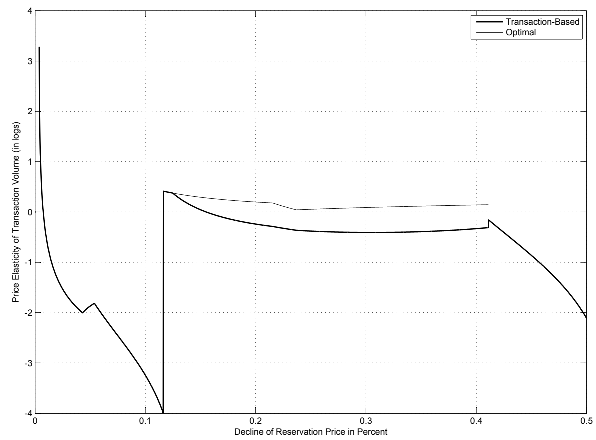
occur, if the short-term house price falls below the original mortgage volume (i.e. the initial house price times its LTV) of a given type of homeowner. The difference between the two defines the loss that the banking sector realises per type of homeowner. Summing over the individual losses returns the aggregate loss of the banking sector. Its equity decreases accordingly.[21] Thus, the banking sector needs to slacken its lending to keep its leverage constant. Following the above pecking order, the banking sector allocates the reduced lending volume to distressed home sales first before distributing the remainder to less affected ones.



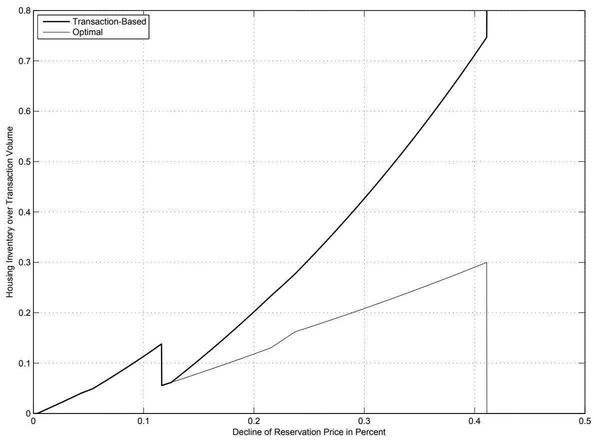
(a) **Bank losses and lack of mortgage volume.**



(b) **Price discount vs. long-run house price.**



(c) **Price elasticity of home sales.**



(d) **Inventory over home sales.**

Figure 1.11: Mortgage losses and house prices. This figure characterises the optimal sales decision of homeowners under crowding-out of non-distressed home sales due to the inefficient provision of lending capacity by the banking sector. The model framework is customised to the specifics of the US housing market. Sections (a) to (d) exhibit different properties of the model: bank losses and the lack of mortgage volume, price discounts, price elasticity and housing inventory. The respective properties are depicted on the vertical axis. The percentage decline in the reservation price is on the horizontal axis. For details on the parameterization please confer to Table A.1 in the appendix.

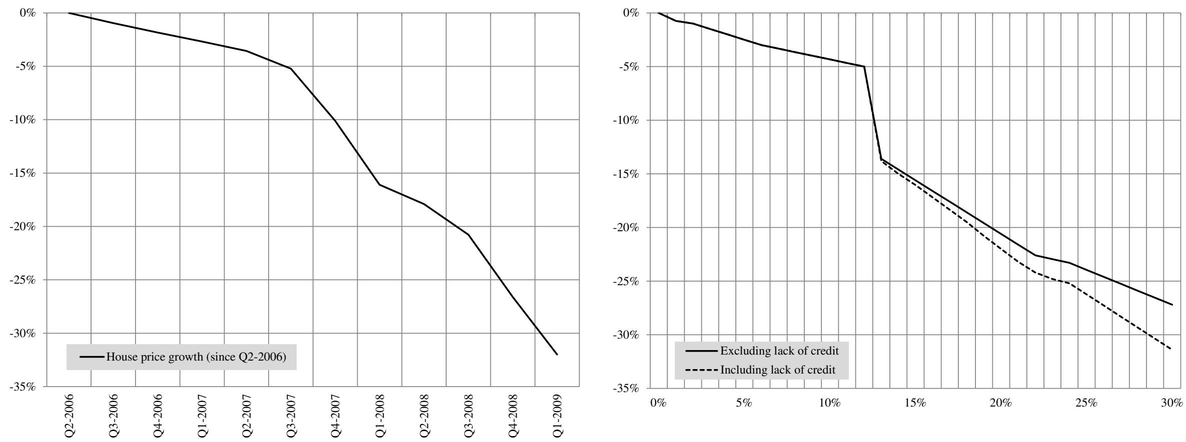
The simulations indicate that losses in the banking sector may impair home sales and

[21] Similar to Hatzius (2008), we implicitly assume that banks are not able to recapitalise instantly to offset their initial losses.

house prices at the same time if the lending capacity becomes insufficient. However, note that the banking sector suffers no losses unless subprime borrowers default (cf. Figure 1.11). As implied by the above pecking order, any lack of lending volume solely impairs the execution of pending sales in the prime segment. Home sales for which no credit is available are suspended. With home sales being skewed in such a way, the *transaction-weighted aggregate house price* also departs downwards from its unconstrained equivalent. Besides, under crowding out, the quantity clearing mechanism dominates the price clearing mechanism. The transaction-based elasticity is not only smaller than without crowding out, but also becomes negative again once the phenomenon comes into effect. However, the most eye-catching consequence, apart from skewed house prices, is the size of the additional ramp-up in inventory formation, once a lack of lending capacity occurs. Hence, the unintended reduction in home sales due to a shortage of available lending volume strains the aggregate house price rather than stabilizing it.

The close resemblance of the observed and the model-implied house price over the crisis period corroborates the perception that the deliberate defaults of homeowners and an insufficient lending volume supported the US housing market collapse. Figure 1.12 exhibits the observed and projected trajectory of US house prices from peak to trough. They reveal an astonishingly close resemblance. In particular, declining house prices gained momentum subsequent to an initial five-percent drop. Moreover, the house price growth temporarily slowed down before accelerating again. This delayed "double drop" matches the idea of deliberately defaulting homeowners in the subprime and prime segments prompting sell-off waves of foreclosed homes. Moreover, this observation suggests a causal link between the severity of a slowdown and the way in which the housing market clears. Small price discounts are compatible with a low overhang and quantity clearing. However, substantial price discounts do not materialise unless a sufficiently large excess supply lets the market clear through prices. Finally, the brief time gap between the first and the second price drop (Q3/2007 and Q3/2008) hints at either an accelerating overhang or a mounting lack of mortgage credit. In our view, these insights underpin the case for the disastrous effects of deliberate defaults and insufficient lending volume on the stability of the US housing market over the course of the recent crisis.

In essence, a disruption in financial intermediation caused by falling house prices could "infect" the price discovery in the housing market even further, because it forces house



(a) US house price growth. **(b) Projected US house price growth.**

Figure 1.12: Observed and projected US house price growth. This figure portrays the observed and projected house price growth from peak to trough during the recent US housing crisis (2006-2009). Growth rates are computed since inception of the crisis (Q2/2006) based on the S&P Case/Shiller National House Price and on simulations of the US-specific heterogeneous model with crowding-out of non-distressed home sales. Data sources: Robert Shiller (www.econ.yale.edu/shiller/data/Fig2-1.xls), own calculations.

prices and home sales below their fundamental levels. Besides, under the given assumptions, the projected bias should define a lower boundary. Since the banking sector is assumed to be uniform, the lending capacity can easily be transferred across segments. However, in reality, the banking sector is fragmented. Hence, a lack of lending capacity might actually harm the housing market more gravely. In fact, there were signs of lacking mortgage volume during the US housing market crash. Professional commentators argued that prospective homebuyers faced serious difficulties in obtaining bank funding to purchase a house, despite very favourable financing terms (CoreLogic, 2010).

1.6 Conclusions

This paper explores how homeowners should optimally respond to the typical excess supply during housing market downturns. Should they sell immediately at potential fire sale prices or should they postpone a sale for some time to sit out the negative consequences of a slowdown? The presented game-theoretical model provides a comprehensive seller-oriented explanation. Homeowners ought to retard a sale, as long as the immediate short-term house price is lower than the expected total cash flows of the property. In this way, homeowners effectively shorten the housing overhang and help to stabilise house prices in the immediate short term. However, under rare circumstances, their financial objective are no longer met. Then, homeowners lose any interest in retarding a sale strategically. The subsequent uncoordinated sell-off sends negative spillovers to other market segments and allows house prices to plummet. Hence, the model establishes a causal link between the severity of slowdowns, the timing of home sales and the way in which housing markets clear.

This constitutes a major extension of our theoretical understanding of housing downturns compatible with observations made over the course of the recent US housing market crash. Under the traditional "quantity clearing mechanism' (Case and Quigley, 2008)', housing downturns would primarily unwind through lower home sales. However, as the final phase of the recent US housing crisis (2006 and 2009) revealed, the house price growth may considerably outpace the depreciation in home sales (cf. Figure 1.1). This decisive experience gives rise to a "price clearing mechanism" (Case and Quigley, 2008). The housing market model presented in this paper is the first to integrate both mechanisms into the same framework.

The numerical simulations further demonstrate that the degree of heterogeneity of the housing market is another relevant factor for the stability of house prices. For instance, on one side, the less fragmented the housing market is, the more stable the aggregate house price is for low to moderate oversupply. On the other side, the house price becomes more vulnerable to substantial excess supply. These two observations reflect that cross-segment competition splits the burden of adjustment across housing segments. This provides homeowners with leeway for responding strategically to even segment-specific downturns. By contrast, the market depth and thus the capacity of the market to absorb an overhang decreases. Hence, a strongly fragmented housing market is more resilient in the presence of a low to moderate housing overhang, but prone to substantial excess supply. The degree of heterogeneity across segments is therefore critical during housing downturns.

Moreover, a US-specific model version imitating the country's 2006-2009 housing crisis shows that high leverage non-recourse mortgages and an undercapitalised banking sector may add to the fragility of the housing market. Each source undermines either the incentive of homeowners to retard a sale or their ability to pursue the optimal sales strategy. First, high-leverage non-recourse mortgages are destabilising, because they facilitate deliberate mass foreclosures at relatively low levels of demand reduction. In fact, US bankruptcy law prevents creditors from seizing the residual property of debtors in the case of default. Homeowners accordingly possess an option to stop serving their mortgage once the expected loan payments surpass the proceeds. Waves of deliberate foreclosures might consequently devastate house prices. The risk is particularly elevated in combination with a high LTV as the incentive to continue with the contract responds sensitively even to small excess supply. Consistent with the empirical evidence, our results corroborate an accelerating fall in house prices (cf. Financial Times, 2008; Huang, 2012) caused by subprime homeowners and a strong negative correlation between house price growth and foreclosure rates (cf. Campbell et al., 2011; Frame et al., 2008; Mian et al., 2014). Second, an undercapitalised banking sector might reinforce house price declines. The reason is that losses in its mortgage portfolio require the banking sector to allocate loans more selectively. Since US commercial banks prioritised distressed home sales during the crisis (Berrospide et al., 2013), non-distressed transactions were crowded out. Thus, the aggregate house price was downward biased. It no longer accurately reflected the sales decision of homeowners, but the insufficient lending capacity of the banking sector.[22] The associated build-up of the housing inventory is consequently inefficient and contaminates house prices. After all, a US-specific housing model illustrates that both high-leverage non-recourse mortgages and an undercapitalised banking sector particularly impaired the stability of the housing market.

Our numerical results further explore possible ways for policy makers to stabilise struggling housing markets via monetary policy, urban policy and financial stimuli by encouraging homeowners to postpone a sale deliberately until house prices recover in the future. The first option is to expand the monetary policy. This would alleviate the opportunity costs of a delayed sale. Homeowners would therefore find it more attractive to retreat from the market temporarily. An advantage of this approach is its comparatively easy implementation. Another option is to incentivise banks financially to prolong outstanding mortgages, giving homeowners more time to postpone a sale. Technically, this option involves negotiations between the parties involved, namely banks and borrowers. The role of policy makers would be to facilitate the negotiations by offering financial stimuli. The last and admittedly most radical option is to reduce abundant supply by demolishing houses in the context of urban policy. However, this instrument should only be carefully used and under very strict conditions. Demand needs to decline either permanently, say

[22] The argument follows those of Shleifer (1992), Kiyotaki and Moore (1997), Krishnamurthy (2003) and Lorenzoni (2008).

following an excessive creation of housing space without sustainable long-term use, or continue to decline in the long-term, similar to an agglomeration steadily losing population over time. Urban planners further need to take steps to avoid excessive demolitions. Moreover, given the apparent interference with private property rights this instrument requires considerable financial resources to earn the consent of affected homeowners. But in any case, monetary policy, urban policy and financial stimuli provide indirect ways for policy makers to stabilise struggling housing markets.

In fact, US policy makers implemented closely related policies over the course of the US housing market crash. In October 2008, the Federal Reserve cut interest rates to historical lows. Among other aims, the objective was to stabilise asset prices, such as house prices.[23] This move was accompanied by purchases of MBS of about USD 1.25 tn.[24] At about the same time, the US federal government implemented the "Troubled Asset Relief Program" worth USD 700 bn (later reduced to USD 475 bn). One of the primary objectives to be achieved by this programme was to "prevent avoidable foreclosures" by purchasing a wide range of assets.[25] Finally, the US housing market crash pushed the city of Detroit over the edge following decades shrinking population and urban decline. In 2010, the city eventually decided to demolish about 10,000 houses to reduce the city's abundant long-term supply of homes (Wall Street Journal, 2010). Hence, US policy makers made considerable use of the policy instruments explored.

Ultimately, the presented game-theoretical framework may be useful in the wider context of capital-intensive and rent-producing durable goods. Beyond housing, this may include freighters, planes, trains or trucks. These industries are also prone to lengthy periods of oversupply, which threaten the immediate short-term prices. An example of such a downturn is the as yet unresolved "Container Crisis". It had its origin in the bubble-like overproduction of container ships accompanied by a sharp contraction of world trade over the course of the global economic crisis of 2009-2010 (Hoffmann, 2010). The author concluded that shipowners indeed responded to the overhang precisely as predicted by

[23] The Federal Reserve noted that "[l]ow interest rates help households and businesses finance new spending and help support the prices of many other assets, such as stocks and houses". Federal Reserve website: http://www.federalreserve.gov/faqs/money_12849.htm

[24] The FRBNY noted that "[t]he goal of the program was to provide support to mortgage and housing markets and to foster improved conditions in financial markets more generally. (...) The FOMC directed the Desk to purchase $1.25 trillion of agency MBS. Actual purchases by the program effectively reached this target". FRBNY website: http://www.newyorkfed.org/markets/mbs_faq.html

[25] Website of the US Treasury: http://www.treasury.gov/initiatives/financial-stability/TARP-Programs/Pages/default.aspx#

the heterogeneous model: they shut down and even demolished ships to reduce the excess supply of cargo space. Hence, the presented model might also be useful for analysing transport economics.

Chapter 2

The Systemic Dimension of Hedge Fund Illiquidity and Prime Brokerage

This chapter is joint work with Frank Hespeler.

The authors thank Tarun Ramadorai for his critical review of this paper.

Abstract

We analyse the potentially vulnerable and systemically relevant financial intermediation chain established by hedge funds and prime brokers in. Our dataset covers the 306 largest global hedge funds and their prime brokers over the period July 2001 to December 2011. The study illustrates that hedge funds and prime brokers act as complementary trading partners in normal times. However, we observe that this form of financial intermediation may be severely impaired in times of market distress. This can be explained by the hoarding of liquid securities by prime brokers who are eager to avert runs by their clients.

2.1 Introduction

The recent global financial crisis is, among other features, characterised by the near drying out of the market for securitised funding Gorton and Metrick (2012). The repo market was among those market segments which were most badly affected. Our analysis highlights a potential reason for that incident: the indispensable flow of collateral assets was severely impaired by the break-down of a financial intermediation chain jointly formed by hedge funds and prime brokers. To shed some light on those events we investigate the dynamic aspects of the vulnerable relationship between hedge funds and prime broker activity by using a heteroskedasticity-robust vector error correction (VEC) model.

Usually, hedge funds deal with prime brokers for the purpose of receiving cash loans which enable them to purchase assets.[26] In this process they frequently pledge previously acquired assets as collateral with prime brokers. In addition, in many cases they authorise prime brokers to re-hypothecate those assets in order to obtain more favourable borrowing terms. Prime brokers exercise this right and enter into repos which are collateralised by their clients' assets. Collateralised lending does not only constitute the main refinancing source of both hedge funds and prime brokers (Singh, 2011), but also turns hedge funds into the major genuine providers of collateral assets to the bilateral repo market (Singh and Aitken, 2010). In addition, this specific form of financial intermediation involves a high degree of maturity transformation. As a matter of fact, according to the Federal Reserve Bank of New York's (FRBNY) primary dealer database (cf. Section 2), in recent years prime brokers were continuously term net lenders and overnight net borrowers. This strategy allows prime brokers to reduce their funding costs and to profit from interest differentials between tenors.

However, for the same two reasons, leverage and maturity transformation, this form of financial intermediation is particularly vulnerable to liquidity shortages and eventually runs. In fact, recent research strongly suggests that these risks materialised over the 2007-2008 global financial crisis, when the market for securitised funding partially ran dry. On this reading, rising haircuts gradually impaired the ability of prime brokers to use securities as collateral to rollover their short-term debt (Brunnermeier, 2009; Gor-

[26] Since hedge funds are fairly unregulated institutional investors and exclusively open to sophisticated investors, they usually apply more aggressive leverage levels and trading strategies than other types of mutual funds. For a more detailed characterisation of hedge funds see King and Maier (2009).

ton and Metrick, 2012). Once haircuts reached a point where the collateral value fell short of the outstanding repo volume, lenders at last had an incentive to call in on all their claims similar to classic depositors (Martin et al., 2012). Beyond that, disconcerted hedge funds wishing to withdraw their liquid wealth from prime brokers susceptible to bankruptcy added another threat to the stability of prime brokers (Brunnermeier, 2009) by repaying loans prematurely and forcing prime brokers to return the collateral. In case the value of the collateral for prime brokers was higher than the margin of the underlying debt contract, this inflicted losses on prime brokers. In line with this argument, Aragon and Strahan (2012) indeed document that clients of Lehman Brothers arriving too late to redeem their assets before the prime broker's bankruptcy, realised significantly lower subsequent returns than their peers. Finally, as Liu and Mello (2011) show, hedge funds are further vulnerable to runs by their investors. In a nutshell, the financial intermediation chain established by prime brokers and hedge funds appears fragile due to their considerable involvement in leverage and maturity transformation.

We contribute to this literature by exploring all aspects of the fragile intermediation chain established by hedge funds and prime brokers in a dynamic setting. For this purpose, we exploit a dataset covering the 306 largest global active hedge funds and their prime brokers over the period July 2001 to December 2011. The dataset includes the five endogenous variables hedge fund illiquidity, prime broker excess profitability and three proxies for prime brokerage activities (lending, financing and securities holdings).

Our results suggest that hedge funds and prime brokers act as complementary trading partners in normal times, i.e. hedge fund illiquidity initiates prime broker activity, which, in turn, raises their excess profitability. However, whenever the volatility of prime broker excess returns and hedge fund illiquidity switched to exceptional high levels during the recent global financial crisis, we discover that this specific form of financial intermediation was severely impaired. Under these conditions, prime brokers' financing activity and securities holdings increased, while their lending did not. At the same time, hedge fund illiquidity rose. This discrepancy indicates that prime brokers hoarded liquid assets. Building on the above findings, the evidence found suggests that during the crisis prime brokers were indeed eager to prevent a run by their clients. But by following this incentive they impaired the flow of collateral assets to the repo market. Thus, it turns out that this particular behaviour of prime brokers adds to systemic risk in securities markets, since, in times of crisis, they have an incentive to withdraw liquidity from an already weakened market. Hence, they potentially impair the value of their clients' assets and contribute to the potential spreading of stress, because, within their decision, they do not consider the negative externalities of their liquidity hoarding on general asset prices.

Our findings reconfirm several empirical results from different strands of previous research. First, we substantiate the view that prime brokers hoarded liquid securities, as was hypothesised by Singh and Aitken (2009a) and actually documented by Berrospide (2012) for commercial banks. Second, the empirical evidence implies that the flow of collateral assets to the repo market came under pressure over the course of the crisis, thereby incentivising hedge funds to deleverage. Earlier studies consistently report that hedge funds deleveraged in the wake of the financial crisis (Ang et al., 2011), while the repo activity of primary dealers considerably declined Adrian and Shin (2010). In fact, Singh and Aitken (2010) compute that the actual reduction in re-hypothecation amounted to roughly USD 2.5 trillion in 2008, of which USD 1.7 trillion stem from major prime brokers alone. We deliver the rationale behind this behaviour. Third, our results provide an explanation for the unusual clustering of hedge fund returns on the height of the crisis (Billio et al., 2012; Boyson et al., 2010). Thus, the compiled empirical evidence sheds new light on the important role of hedge funds and prime brokers in the recent financial crisis.

The paper proceeds as follows. Section 2.2 describes our set of endogenous variables and control variables. In Section 2.3 we explain the model selection procedure. Next, Section 2.4 characterises the intermediation chain composed of hedge funds and prime brokers by examining the dynamic interaction of hedge fund illiquidity and prime brokerage. Various robustness checks are presented in Section 2.5. Section 2.6 briefly discusses our findings in light of systemic risk, and Section 2.7 concludes.

2.2 Data

Our paper is based on monthly data from July 2001 to December 2011 and uses five endogenous variables for its econometric model. This data is presented below.[27]

[27] If not otherwise indicated all data originates from Thomson Datastream.

2.2.1 Hedge Funds — an Illiquidity Premium

For the construction of an illiquidity premium of the hedge fund sector, i.e. a measure for that fraction of the sector's profit which can be explained by its willingness to hold illiquid assets, this paper employs consolidated data on the 100 largest funds identified by assets under management (AuM) as of December 2011, out of each of four hedge fund databases: Barclayhedge, Eurekahedge, Hedge Fund Research, TASS. The use of consolidated data helps to avoid any selection bias generated by a limited coverage of the hedge fund universe in individual data sources (Fung and Hsieh, 2001; Patton and Ramadorai, 2013; Joenvaara et al., 2012). On the other hand, consolidation allows for data overlaps. To eliminate those, a structured consolidation process similar to those used in Patton and Ramadorai (2013) and Joenvaara et al. (2012) is used to identify and remove duplicates.[28] Following this method, our final dataset comprises 306 hedge funds, which all belong to the so-called "billion dollar club"[29] frequently used for classifying funds into risk categories.

We restrict our analysis to large hedge funds, because they exhibit some important characteristics of systemically important financial institutions (SIFI). As King and Maier (2009) explain, i.) large hedge funds impose a *concentrated risk* on their prime brokers, ii.) they are *highly interconnected* by maintaining many prime broker relations, and iii.) they provide liquidity in *global asset markets*. However, the focus on large hedge funds implies potential deviations in the composition of our sample from the hedge fund universe. Nevertheless, the method provides the advantage that our dataset exclusively covers large and currently active funds which are important for systemic risk analysis.

Based on this dataset we aggregate returns using uniform weights since alternative weights, such as net asset values or AuM turn out to be unreliable or biased by differing leverage levels of funds (Ang et al., 2011).[30] To control for hedge fund-specific liquidity factors and the capability to generate alpha, we regress the aggregated hedge fund return on five asset-based strategy factors (Fung and Hsieh, 2001), the negative portion of the MSCI world index as an approximation of a put option (Agarwal and Naik, 2004) and a constant.[31] The resulting residual (HFILLIQ) comprises roughly 80% of the total variation

28 A more detailed description is provided in the appendix.
29 See Edelman et al. (2012)
30 Until October 1, 2011, the popular HFR index was computed using uniform weights.
31 The asset-based strategy factors were collected from David Hsieh's website:

and reflects the return attributed to hedge funds' illiquid asset holdings, as the mentioned factors provide liquidity insurance whenever market liquidity is low. By removing their contribution from hedge fund returns we thus obtain the intrinsically illiquid part.[32] This variable is the first in our set of endogenous variables.

2.2.2 Prime Brokers

To describe the performance and activities of prime brokers we use several variables. As a performance measure the excess return of prime brokers relative to commercial banks is employed. Therefore, we first identify the reported prime broker relations within our hedge fund sample. Then, we aggregate the monthly stock price returns for those prime brokers for which data is available, to a uniformly weighted index return.[33] Since many prime brokers also offer other banking services, it is important to filter out the excess return from prime brokerage (PBER). For this purpose, we regress the aggregated prime broker return on the return of the Datastream global bank index and use the residual as our variable PBER.[34] This last step reveals a high contribution of banking activities outside of prime brokerage for our constituents' performance (adj. R-Squared about 0.87).

Furthermore, we capture prime brokers' securities trading activities by three variables reported by the FRBNY's primary dealer database.[35] Our first variable, the net outright position of primary dealers (NETPOS), describes the excess volume of securities held to meet delivery obligations (Adrian and Fleming, 2005). This position measures the risk-taking behaviour of primary dealers. Net financing defined as the difference between outgoing and incoming securities approximates the financing and lending activity of prime brokers. When differentiating between overnight and term agreements, it turns out that prime brokers are overnight net borrowers and term net lenders which is why we denote both indicators correspondingly FINANCING and LENDING. This first empiric evidence

http://faculty.fuqua.duke.edu/ dah7/DataLibrary/TF-FAC.xls

32 Getmansky et al. (2004) propose the serial correlation of hedge fund returns as an alternative measure of portfolio illiquidity attributable to difficult-to-market or immobile asset holdings. A closely related paper following this approach is Kruttli et al. (2013). Our approach goes beyond this illiquidity concept, because besides the described filtration our econometric model automatically captures serial correlation in the sense of Getmansky et al. (2004).

33 For details on prime brokers please refer to the appendix.

34 An alternative methodology which aggregates the residuals generated by regressing individual returns on the Datastream global bank index, yielded weak results, as outliers tend to dominate the sample.

35 The majority of prime brokers in our sample also registers with the FRBNY as primary dealers and thus contributes to the database.

indicates that prime brokers generate profits by engaging in maturity transformation.[36] All three variables are normalised as of July 2001.

2.2.3 Macroeconomic and Financial Control Variables

As control variables we include several macroeconomic and financial indicators. To consider the frequent use of mortgage backed securities as collateral in the repo market (Adrian and Fleming, 2005) we use the monthly growth of the S&P Case/Shiller 20-city composite house price index (HOUSE). In addition, the yearly growth of the same index which cannot be explained by monthly growth (roughly 49% of variation), measures potential asset price bubbles (HOUSETREND). The annual growth of the MSCI World total-return index (EQUITY) proxies the expected profitability of firms and global economic activity. The monthly growth of the Barclays aggregate bond index (BOND) grasps global financial market conditions and yield trends. To account for commodity price fluctuations that affect global economic growth, we also factor in the annual gold price (GOLD) and oil price (OIL). The monthly growth of the TED spread (LIQRISK) and Moody's Baa spread (DEFRISK) control for funding liquidity risk and default risk. As a measure of currency risks, we consider the EUR/USD exchange rate (CURRENCY).[37]

2.2.4 Turmoil Control Variables

Periods of financial turmoil are reportedly related to unusual negative hedge fund returns (Billio et al., 2012; Boyson et al., 2010) and prime broker difficulties (Aragon and Strahan, 2012). Therefore, following the approach of Hendry and Juselius (2001), we include two transitory blip variables to account for *unexpected extreme movements in the endogenous variables*. Both blip variables are constructed from the residuals of the estimated VEC model (cf. Section 3); one using the residuals of the performance proxies (RETURN VOLA: PBER, HFILLIQ) and the other those of prime broker activity (ACTIVITY VOLA: LENDING, NETPOS, FINANCING). A turmoil state is a situation, in which the variances of the residuals of all variables associated with the one of the groups described above simultaneously fall into the highest deciles at a given point in time. The

[36] For a detailed discussion on the data reported in the FRBNY's primary dealer database please see Adrian and Fleming (2005)

[37] Please refer to Table A.1 in the appendix for an exact definition of the various exogenous variables.

final blip variables take on the value 1 if the associated group *enters* into a state of high volatility, -1 if the associated group *leaves* a state of high volatility and 0 otherwise. By this procedure we are able to factor in the potentially disruptive effect of turmoil-related events without impairing the model's stationarity. Incidences of volatility switches are rare and mostly occur in times of financial turmoil, i.e. between 2007 and 2011.

2.3 Model Selection

An analysis of the raw data of our endogenous variables reveals that all variables are autocorrelated and three of them clearly exhibit non-stationarity (LENDING, NETPOS, FINANCING). Beyond that, HFILLIQ shows signs of non-stationarity as heteroskedasticity-robust auxiliary regressions on a constant and time trend are nearly significant on the 5% level. We therefore opt for a VEC model (Johansen and Juselius, 1990) for estimation purposes,

$$\Delta y_t = \alpha(c' + \beta' y_{t-1}) + \sum_{i=1}^{p-1} \Phi_i^* \Delta y_{t-i} + BX_t + \epsilon_t, \tag{2.1}$$

where y_t denotes a vector of endogenous variables, X_t the set of exogenous information and p the lag order of the associated vector autoregressive representation (VAR). In what follows, we apply our set of endogenous and control variables.

In order to determine which specification fits our dataset best, we initially evaluate 60 different model estimates based on a large set of criteria. Those include the cointegration rank statistics based on Johansen (1991) (maximum likelihood, trace statistic, Akaike and Schwarz information criteria), measures for the model fit (average adjusted R-Squared), test statistics for the residuals (autocorrelation, heteroskedasticity, lag exclusion, normality) and structural break statistics (Chow breakpoint tests). The alternatives differ by lag length, cointegration rank and specification of the cointegration equation.

Our results displayed in Table 2.2 suggest strong serial correlation in the residuals of models including one or three lags. They are therefore rejected.[38] From the remaining

[38] We acknowledge that critical values of the maximum likelihood statistic and trace statistic based on Johansen (1991) are potentially distorted as a result of the inclusion of exogenous factors. However, given the consistency with either the Akaike or Schwarz information criterion and the tests on residuals and model robustness both rank criteria appear to operate fairly well.

Table 2.1: Data characteristics. This table portrays various characteristics of the endogenous and exogenous variables. Descriptive statistics include the mean, median, minimum, maximum and standard deviation. The skewness, kurtosis and p-values of the Jarque-bera statistics are reported to test for normality. The p-values of the Ljung-Box test statistics give indicative information on serial correlation. Assessments of individual and joint stationarity are based on p-values of the Augmented-Dickey Fuller and Fisher-ADF tests (both with constant). The correlations between the endogenous and exogenous variables illustrate co-movement patterns.

	Endogenous variables					**Exogenous variables**										
Descriptive Statistics	PBER	HFILLIQ	LENDING	NETPOS	FINANCING	HOUSE	HOUSE-TREND	EQUITY	BOND	GOLD	OIL	DEF-RISK	LIQ-RISK	CURR-ENCY	RET. VOLA	ACT. VOLA
Mean	-0.537	0.000	2.097	1.963	1.944	2.735	0.128	5.264	0.023	18.863	20.160	0.411	5.869	-0.319	0.000	0.000
Median	-0.563	0.037	2.239	1.908	1.844	4.456	0.381	11.616	0.080	17.237	24.000	-0.641	1.828	-0.456	0.000	0.000
Max	8.544	2.546	3.327	3.768	3.670	17.121	1.993	64.283	2.663	52.459	113.576	39.992	198.176	9.743	1.000	1.000
Min	-8.174	-2.480	0.884	0.822	1.000	-19.006	-2.790	-48.906	-2.736	-8.054	-61.373	-20.819	-69.231	-9.387	-1.000	-1.000
Std. dev.	2.493	1.103	0.654	0.643	0.603	10.943	1.155	22.255	0.873	13.484	35.969	7.357	38.536	3.148	0.219	0.179
Normality (Jarque-Bera)																
Skewness	0.046	-0.094	-0.084	0.401	0.638	-0.495	-0.661	-0.327	-0.235	0.434	-0.214	1.333	2.253	0.398	0.000	0.000
Kurtosis	4.693	2.680	1.959	2.548	2.892	2.077	2.624	2.821	3.157	2.675	2.720	8.922	11.511	3.959	21.000	31.500
Probability	0.001	0.696	0.054	0.108	0.013	0.008	0.007	0.300	0.526	0.105	0.503	0.000	0.000	0.017	0.000	0.000
Autocorrelation (Ljung-Box)																
LB(1)	0.460	0.070	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.043	0.826	0.000	0.000
LB(2)	0.759	0.114	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.092	0.878	0.000	0.000
LB(3)	0.068	0.070	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.098	0.375	0.000	0.000
Unit root																
Individual: Augmented Dickey-Fuller (ADF)																
Level	0.000	0.000	0.557	0.457	0.570	0.000	0.002	0.100	0.000	0.005	0.031	0.000	0.000	0.000	0.000	0.000
Difference	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Common: Fisher-ADF																
Level	0.000	0.000	0.000	0.000	0.000	0.065	0.000	0.013	0.003	0.061	0.010	0.000	0.000	0.000	0.000	0.000
Difference	0.000	0.000	0.000	0.000	0.000	0.001	0.012	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Correlations																
PBER	1.000					0.180	-0.105	-0.128	-0.008	0.035	-0.055	0.053	0.062	-0.091	-0.024	-0.263
HFILLIQ	-0.139	1.000				0.033	0.010	-0.185	0.239	-0.365	-0.349	-0.243	-0.115	-0.156	0.244	0.095
LENDING	0.011	-0.056	1.000			-0.314	-0.574	0.028	-0.140	0.264	0.032	0.118	-0.025	0.128	0.066	0.070
NETPOS	-0.090	0.008	0.760	1.000		-0.353	-0.687	-0.027	0.087	0.318	0.110	0.248	0.064	0.053	0.060	0.093
FINANCING	-0.037	0.018	0.875	0.845	1.000	-0.299	-0.687	-0.069	-0.163	0.263	0.049	0.241	0.051	0.047	0.068	0.072
Observations	126	126	126	126	126	126	126	126	126	126	126	126	126	126	126	126

Table 2.2: Selection of VEC model. This table reports cointegration rank criteria and diagnostic test statistics on a variety of model specifications ordered by lag length, cointegration rank and type of estimation. Estimation is based on Johansen and Juselius (1990). The type of estimation represents the treatment of constants and trends in the long-run and short-run part of the VEC model (1: No constants, no trends; 2: Constant in long-run part; 3: Two constants in long-run and short-run part; 4: Two constants and linear trend; 5: Two constants and quadratic trend). The maximum eigenvalue statistic (ME), trace statistic (TR), Akaike (AIC) and Schwarz (SIC) information criteria are cointegration rank criteria (Johansen and Juselius, 1988). Residual diagnostic tests on serial correlation (Lagrange Multiplier test: LM(p)) heteroskedasticity (White test), normality (generalised Jarque-Bera (Urzua) statistic) and lag exclusion (Wald test: LE(p)) are based on Luetkepohl (2005). The cumulated number of rejections of Chow breakpoint tests (July 2005 and December 2007) indicate model instability. *** (**,*) denotes significance at the 1% (5%, 10%) level.

Specifications			Cointegration Rank				Model Fit	Autocorrelation		
Lag	Rank	Type	ME	TR	AIC	SIC	aver. adj. R2	LM(1)	LM(2)	LM(3)
1	1	1	2	2	6.620	7.416	0.354	0.000	0.000	0.000
		2	3	3	6.557	7.375	0.353	0.000	0.000	0.000
		3	5	3	6.608	7.518	0.347	0.000	0.000	0.000
		4	4	4	6.576	7.509	0.356	0.000	0.000	0.000
		5	4	4	6.627	7.651	0.352	0.000	0.000	0.000
	2	1	2	2	6.290	7.314	0.406	0.000	0.000	0.000
		2	3	3	6.241	7.310*	0.406	0.000	0.000	0.000
		3	5	3	6.285	7.422	0.400	0.000	0.000	0.000
		4	4	4	6.227	7.410	0.422	0.000	0.000	0.000
		5	4	4	6.265	7.515	0.420	0.000	0.000	0.000
	3	1	2	2	6.315	7.566	0.407	0.000	0.000	0.000
		2	3	3	6.169	7.488	0.446	0.000	0.006	0.000
		3	5	3	6.197	7.562	0.441	0.000	0.007	0.000
		4	4	4	6.012	7.444	0.500	0.001	0.051	0.000
		5	4	4	6.036	7.514	0.496	0.000	0.046	0.000
	4	1	2	2	6.440	7.919	0.403	0.000	0.000	0.000
		2	3	3	6.252	7.821	0.458	0.000	0.053	0.000
		3	5	3	6.264	7.856	0.453	0.000	0.056	0.000
		4	4	4	5.976*	7.659	0.509	0.005	0.134	0.000
		5	4	4	5.987	7.693	0.504	0.004	0.129	0.000
2	1	1	2	2	5.733	7.105	0.593	0.008	0.360	0.003
		2	2	2	5.740	7.135	0.590	0.010	0.228	0.003
		3	2	2	5.792	7.278	0.590	0.017	0.382	0.008
		4	2	3	5.797	7.306	0.588	0.045	0.380	0.054
		5	3	3	5.841	7.442	0.589	0.034	0.476	0.018
	2	1	2	2	5.377	6.977*	0.633	0.077	0.362	0.059
		2	2	2	5.368	7.015	0.633	0.068	0.356	0.135
		3	2	2	5.409	7.124	0.629	0.102	0.350	0.159
		4	2	3	5.390	7.151	0.630	0.090	0.460	0.184
		5	3	3	5.434	7.263	0.627	0.093	0.424	0.218
	3	1	2	2	5.423	7.252	0.635	0.086	0.276	0.074
		2	2	2	5.398	7.296	0.637	0.119	0.368	0.129
		3	2	2	5.426	7.369	0.634	0.154	0.356	0.135
		4	2	3	5.353*	7.365	0.637	0.104	0.615	0.136
		5	3	3	5.383	7.440	0.634	0.106	0.628	0.158
	4	1	2	2	5.562	7.620	0.632	0.090	0.236	0.070
		2	2	2	5.552	7.701	0.634	0.122	0.352	0.133
		3	2	2	5.567	7.739	0.631	0.127	0.342	0.129
		4	2	3	5.461	7.724	0.636	0.070	0.604	0.047
		5	3	3	5.475	7.761	0.633	0.071	0.622	0.055
3	1	1	2	2	5.848	7.801	0.594	0.002	0.367	0.066
		2	2	2	5.835	7.812	0.588	0.009	0.034	0.053
		3	2	2	5.878	7.947	0.584	0.262	0.006	0.066
		4	2	2	5.834	7.925	0.590	0.554	0.020	0.170
		5	3	3	5.892	8.076	0.588	0.611	0.023	0.174
	2	1	2	2	5.562	7.745*	0.631	0.457	0.129	0.096
		2	2	2	5.549	7.779	0.631	0.537	0.083	0.102
		3	2	2	5.586	7.884	0.627	0.638	0.087	0.101
		4	2	2	5.550	7.894	0.628	0.555	0.169	0.208
		5	3	3	5.593	8.006	0.624	0.594	0.157	0.245
	3	1	2	2	5.623	8.036	0.632	0.484	0.080	0.104
		2	2	2	5.593	8.075	0.635	0.612	0.102	0.138
		3	2	2	5.621	8.149	0.632	0.650	0.097	0.127
		4	2	2	5.529*	8.127	0.634	0.645	0.119	0.188
		5	3	3	5.558	8.201	0.631	0.661	0.136	0.232
	4	1	2	2	5.755	8.398	0.629	0.512	0.071	0.101
		2	2	2	5.739	8.474	0.631	0.631	0.108	0.180
		3	2	2	5.752	8.510	0.628	0.659	0.107	0.182
		4	2	2	5.620	8.470	0.635	0.609	0.152	0.230
		5	3	3	5.633	8.506	0.631	0.624	0.174	0.279

Table 2.2 continued

Specifications			Heteroskedasticity	Normality			Lag exclusion			Robustness		
Lag	**Rank**	**Type**	**Prob.**	**Prob.**	**Skewness**	**Kurtosis**	**LE(1)**	**LE(2)**	**LE(3)**	**10%**	**5%**	**1%**
1	1	1	0.000	0.728	0.409	0.630	0.000			17	4	0
		2	0.002	0.768	0.232	0.729	0.000			3	0	0
		3	0.003	0.848	0.283	0.802	0.000			0	0	0
		4	0.009	0.622	0.257	0.789	0.000			0	0	0
		5	0.005	0.542	0.350	0.700	0.000			0	0	0
	2	1	0.000	0.001	0.118	0.306	0.000			0	0	0
		2	0.001	0.003	0.069	0.406	0.000			0	0	0
		3	0.001	0.009	0.074	0.466	0.000			0	0	0
		4	0.004	0.102	0.069	0.620	0.000			0	0	0
		5	0.003	0.069	0.111	0.593	0.000			0	0	0
	3	1	0.003	0.003	0.054	0.354	0.000			0	0	0
		2	0.029	0.010	0.036	0.355	0.051			0	0	0
		3	0.030	0.024	0.040	0.389	0.059			0	0	0
		4	0.019	0.010	0.004	0.087	0.161			0	0	0
		5	0.015	0.003	0.005	0.067	0.146			0	0	0
	4	1	0.004	0.001	0.068	0.253	0.000			0	0	0
		2	0.045	0.022	0.008	0.324	0.325			0	0	0
		3	0.049	0.049	0.009	0.354	0.348			0	0	0
		4	0.128	0.018	0.001	0.125	0.366			0	0	0
		5	0.097	0.009	0.002	0.114	0.361			0	0	0
2	1	1	0.004	0.265	0.249	0.751	0.000	0.000		0	0	0
		2	0.008	0.370	0.208	0.709	0.000	0.000		0	0	0
		3	0.006	0.317	0.255	0.755	0.000	0.000		0	0	0
		4	0.002	0.006	0.210	0.278	0.000	0.000		0	0	0
		5	0.002	0.050	0.314	0.658	0.000	0.000		0	0	0
	2	1	0.009	0.104	0.098	0.295	0.000	0.000		8	2	0
		2	0.010	0.099	0.061	0.286	0.000	0.000		2	0	0
		3	0.010	0.190	0.061	0.315	0.000	0.000		2	0	0
		4	0.016	0.053	0.118	0.380	0.000	0.000		0	0	0
		5	0.017	0.045	0.141	0.311	0.000	0.000		0	0	0
	3	1	0.055	0.080	0.033	0.044	0.000	0.000		8	4	0
		2	0.060	0.068	0.042	0.109	0.000	0.000		8	8	0
		3	0.060	0.129	0.046	0.117	0.000	0.000		8	7	0
		4	0.110	0.019	0.004	0.030	0.000	0.000		8	6	0
		5	0.040	0.015	0.005	0.033	0.000	0.000		7	3	0
	4	1	0.029	0.078	0.050	0.030	0.000	0.000		7	1	0
		2	0.035	0.053	0.050	0.060	0.000	0.000		8	8	0
		3	0.037	0.068	0.045	0.058	0.000	0.000		8	3	0
		4	0.122	0.017	0.003	0.027	0.000	0.000		8	7	0
		5	0.038	0.014	0.003	0.029	0.000	0.000		7	3	0
3	1	1	0.049	0.151	0.147	0.566	0.000	0.000	0.254	8	6	0
		2	0.058	0.047	0.130	0.435	0.000	0.000	0.150	9	7	4
		3	0.031	0.007	0.191	0.274	0.000	0.000	0.143	8	6	4
		4	0.022	0.001	0.353	0.225	0.000	0.000	0.102	0	0	0
		5	0.013	0.001	0.444	0.239	0.000	0.000	0.108	0	0	0
	2	1	0.059	0.358	0.252	0.482	0.000	0.000	0.824	0	0	0
		2	0.044	0.379	0.165	0.507	0.000	0.000	0.836	0	0	0
		3	0.043	0.423	0.171	0.530	0.000	0.000	0.831	0	0	0
		4	0.039	0.453	0.229	0.487	0.000	0.000	0.631	0	0	0
		5	0.040	0.530	0.327	0.543	0.000	0.000	0.639	0	0	0
	3	1	0.119	0.247	0.117	0.187	0.000	0.000	0.891	1	0	0
		2	0.068	0.164	0.098	0.280	0.000	0.000	0.890	1	0	0
		3	0.068	0.195	0.110	0.287	0.000	0.000	0.900	1	0	0
		4	0.052	0.121	0.021	0.022	0.000	0.000	0.721	1	0	0
		5	0.036	0.135	0.030	0.023	0.000	0.000	0.724	0	0	0
	4	1	0.074	0.269	0.264	0.138	0.000	0.000	0.868	0	0	0
		2	0.057	0.182	0.178	0.205	0.000	0.000	0.865	3	0	0
		3	0.056	0.211	0.170	0.227	0.000	0.000	0.870	0	0	0
		4	0.061	0.127	0.025	0.024	0.000	0.001	0.654	3	0	0
		5	0.031	0.143	0.034	0.025	0.000	0.001	0.659	0	0	0

specifications we subsequently exclude those for which our ME and TR cointegration rank criteria are inconsistent. Only four models pass this test. Neither the average model fit[39], nor the information criteria or residual tests provide conclusive evidence in favour of any of these four specifications. However, the Chow breakpoint test on structural breaks indicate that the most robust and parsimonious model features two cointegration equations including a constant.[40] Thus, we choose the specification with two cointegration equations including also constants.

Interestingly, the test results in Table 2.2 indicate no violation of the normality assumption despite significant heteroskedasticity. Indeed, a subsequent visual inspection suggests that the residuals may occasionally cluster. Hence, the model standard errors tend to underestimate the true standard deviation. This is why we switch to heteroskedasticity-robust estimation procedures following the methodology provided in Newey and West (1987), and present only results corrected for heteroskedasticity issues. As an additional precaution we completely ignore the 10% significance level for statistical inference.

Finally, we employ Granger causality tests[41] in order to explore whether lagged endogenous variables are contributing to the forecast of contemporaneous realisations of the other endogenous variables. Given our VEC specification the test considers two lags. The results presented in Table 2.3 confirm that the chosen specification is appropriate, since each of the significant parameters in the short-run equation (cf. Table 2.4 below) is matched by some forecasting power of the respective pair of lagged variables.

Table 2.3: Granger causality. This table depicts Wald test results on granger causality (block exogeneity). Reported values are the p-values of the null hypothesis of no Granger causality. *** (**, *) indicates statistical significance at the 1% (5%, 10%) level.

	PBER	**HFILLIQ**	**LENDING**	**NETPOS**	**FINANCING**
PBER	—	0.903	0.358	0.165	0.202
HFILLIQ	0.500	—	**0.092***	0.913	0.223
LENDING	0.241	**0.068***	—	**0.000*****	**0.000*****
NETPOS	0.811	0.499	**0.003*****	—	**0.023****
FINANCING	0.378	0.380	0.324	0.178	—
JOINT	0.616	0.262	**0.000*****	**0.000*****	**0.000*****

39 Despite the non-stationary nature of some of the endogenous variables, the adjusted R-Squared delivers some information here, since the model fit never exceeds an adjusted R-Squared of 70% neither in VAR-form nor in VEC-form.

40 Each restricted model requires a minimum of 48 dated observations. Given that all suspected breakpoints materialise when the number of required observations converges to that minimum, while only few rejections are significant at the 1% level, the results suggest a generally high level of model robustness.

41 Please note that the error correction terms and therefore the cointegration equations are excluded in the tests.

2.4 The Dynamic Interaction of Hedge Fund Illiquidity and Prime Brokerage

We structure the analytical results presented below along our five main conclusions. Each of those is individually connected to the empirical evidence. This evidence comprises the model's cointegration and error correction parts as well as impulse responses to shocks on the endogenous variables. To interpret how these shocks disseminate in the system we perform variance decompositions, which also help to mitigate the endogeneity problem inherent in all VAR models by providing some idea about eventual causalities within the system. For the sake of brevity, we ignore variables whose contribution to the variance of another variable stays below 10%. Within the analysis of impulse responses and variance decompositions we account for different risk dimensions and sources—i.e. shocks to hedge funds, money markets and prime brokers' risk aversion—by changing the ordering in which shocks are able to affect our endogenous variables.

2.4.1 In Periods with no Stress in Financial Markets, Hedge Funds and Prime Brokers Act as Complementary Trading Partners.

Periods without exceptionally high level of financial distress tend to be depicted by the model's cointegration equation, expressing the model's long-run trend. This view, which departs from the traditional perspective, reflects that the two blip variables in the short-run equation are specifically designed to account for financial market turbulences. Therefore, the effect of financial turbulences on the long-run equation should be limited to a minimum.

An accurate economic interpretation of this cointegration equation requires an economically reasonable normalisation. We select prime broker excess returns and hedge fund illiquidity as normalisation variables, because both are likely to depend on the securities trading activities involved in prime brokerage.[42] The resulting cointegration equations

[42] While it seems at first glance odd to include stationary variables in the cointegration equation, the use of the less non-stationary variables as normalization variables has the advantage that the interdependence between our non-stationary business activity variables is not restricted. Hence, we do not fix down the exogenous driving process to an arbitrarily chosen variable. In addition, we observe that in the first cointegration equation we encounter an estimator for the variable FINANCING which is on the border of significance. Assuming significance for that border case, the resulting parameter almost completely compensates for the negative influence of LENDING on PBER. Hence, PBER would remain a stationary process.

are,

$$\begin{pmatrix} PBER_t \\ HFILLIQ_t \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \end{pmatrix} \begin{pmatrix} LENDING \\ NETPOS \\ FINANCING \end{pmatrix}. \tag{2.2}$$

The estimates of the long-run relations reported in Table A.6 suggest that both are economically relevant and plausible. The first reflects a positive long-run link between the lending activity and excess returns of prime brokers. Prime brokers benefit from granting more collateralised loans or performing more securities lending. By implication, excess returns of prime brokers should rise with an expansion of their balance-sheets which indicates the exploitation of economies of scale. The second link reveals that hedge fund illiquidity positively relates to the net position and financing activity of prime brokers, but negatively to their lending activity. Thus, if prime brokers accept higher risks associated with securities holdings and increase their overnight liabilities, hedge funds earn higher returns attributable to portfolio illiquidity due to an increase in the demand for illiquid assets. Similarly, an increase in prime brokers' balance sheets driven by additional intermediation generates a positive net effect for hedge funds' excess returns. But an isolated increase in the lending volume of prime brokers reduces hedge funds' excess return on illiquidity, since higher indebtedness tends to raise haircuts and tightens borrowing conditions. Thus, in general, hedge funds as well as prime brokers generally profit from an extension of the volume transmitted through this financial intermediation chain.

Our results indicate that the benefits from prime brokerage accrue to a larger extent to prime brokers than to their hedge fund clients. This is indicated by a sizeable negative constant in the equation for hedge funds' excess returns (-1.454) and the relative size of the estimators in the two cointegration equations. In addition, the net benefit of lending also clearly favours prime brokers over hedge funds (1.446 vs. -0.740). However, an expansion in the balance sheet of prime brokers due to financial intermediation (LENDING, FINANCING) benefits hedge funds slightly more than prime brokers (0.093 vs. 0.054). Thus, hedge funds pay a substantial premium on the access to term liquidity, but still benefit from an increase in the scale of the transfer of funds from repo markets via prime brokers to themselves. Since both cointegration equations negatively feed back into the short-run (cf. Table A.6), an expansion of the intermediation activity results in moderating effects on excess returns in case those are above their long-run trends. Hence, in general terms, the argument of increasing marginal costs of financial intermediation applies to the business model in the short run.

The central position of prime brokers is also reconfirmed by netting out the feed-back from the first cointegration equation and serial correlation (0.275) in the short-run equation determining prime brokers' excess returns. The serial correlation is substantially positive

Table 2.4: VEC model estimates. This table contains VEC model estimates:

$$\Delta y_t = \alpha(c' + \beta' y_{t-1}) + \sum_{i=1}^{p-1} \Phi_i^* \Delta y_{t-i} + BX_t + \epsilon_t,$$

where y_t = [PBER, HFILLIQ, LENDING, NETPOS, FINANCING]$_t$ denotes a vector of endogenous variables and X_t = [HOUSETREND, HOUSE, EQUITY, BOND, GOLD, OIL, DEFRISK, LIQRISK, CURRENCY, RETURN VOLA, ACTIVITY VOLA]$_t$ the set of exogenous variables. Estimation is based on Johansen and Juselius (1990). The adj. R-squared informs about the overall model fit. *** (**) indicates statistical significance at the 1% (5%) level. Standard errors are heteroskedasticity and autocorrelation robust (Newey and West, 1987).

Panel A: Long-run relationship

	LENDING	NETPOS	FINANCING	Constant
PBER	1.446	-0.096	-1.392	-0.811
HFILLIQ	-0.740	0.978	0.833	-1.454

Panel B: Short-run relationship

	PBER	**HFILLIQ**	**LENDING**	**NETPOS**	**FINANCING**
Error Correction 1	**-1.262*** **	0.009	-0.021	-0.008	-0.025
	(-5.01)	(0.08)	(-0.73)	(-0.29)	(-0.96)
Error Correction 2	0.314	**-1.045*** **	-0.060	0.056	-0.017
	(0.70)	**(-5.48)**	(-1.17)	(1.12)	(-0.35)
PBER(-1)	0.304	-0.016	**0.021** **	0.009	0.016
	(1.33)	(-0.49)	**(2.14)**	(0.64)	(1.38)
PBER(-2)	**0.275*** **	0.000	0.010	0.018	**0.017** **
	(3.83)	(0.01)	(1.24)	(1.57)	**(2.26)**
HFILLIQ(-1)	-0.262	-0.042	**0.062** **	0.010	0.035
	(-0.98)	(-0.34)	**(2.09)**	(0.39)	(1.54)
HFILLIQ(-2)	-0.237	**-0.103** **	**0.052** **	0.010	**0.037** **
	(-1.90)	**(-2.07)**	**(2.52)**	(0.48)	**(2.11)**
LENDING(-1)	0.511	-0.125	**-0.600*** **	**-0.393*** **	**-0.366*** **
	(0.44)	(-0.29)	**(-4.60)**	**(-3.10)**	**(-2.61)**
LENDING(-2)	**2.338*** **	**-1.282*** **	**-0.801*** **	**-0.598*** **	**-0.564*** **
	(4.48)	**(-6.41)**	**(-13.57)**	**(-9.76)**	**(-8.55)**
NETPOS(-1)	-0.496	-0.510	**-0.429*** **	-0.226	**-0.292** **
	(-0.39)	(-1.08)	**(-2.73)**	(-1.68)	**(-2.37)**
NETPOS(-2)	0.619	-0.329	**-0.324*** **	**-0.433*** **	**-0.219*** **
	(1.10)	(-1.56)	**(-4.42)**	**(-6.79)**	**(-3.80)**
FINANCING(-1)	-0.631	0.178	0.007	-0.341	-0.277
	(-0.36)	(0.28)	(0.03)	(-1.64)	(-1.46)
FINANCING(-2)	**-3.172*** **	**1.272*** **	**0.410*** **	**0.267*** **	0.102
	(-4.17)	**(4.70)**	**(4.82)**	**(2.98)**	(1.26)
HOUSETREND	**0.068*** **	**0.066*** **	**0.010*** **	0.005	**0.009*** **
	(2.61)	**(8.11)**	**(4.60)**	(1.85)	**(4.26)**
HOUSE	-0.145	**0.307*** **	0.036	-0.005	0.019
	(-0.84)	**(3.94)**	(1.54)	(-0.26)	(0.99)
EQUITY	**-0.034*** **	0.002	-0.001	-0.001	-0.001
	(-3.37)	(0.41)	(-0.91)	(-0.52)	(-0.98)
BOND	-0.238	0.116	0.025	0.011	0.009
	(-1.11)	(1.08)	(0.77)	(0.43)	(0.32)
GOLD	0.017	**-0.027*** **	0.000	0.002	0.001
	(1.41)	**(-7.28)**	(0.40)	(1.78)	(0.58)
OIL	0.000	**-0.010*** **	-0.001	0.000	0.000
	(0.06)	**(-4.16)**	(-0.85)	(0.67)	(-0.34)
DEFRISK	0.029	**-0.031** **	0.002	**0.013*** **	**0.005** **
	(0.96)	**(-2.39)**	(0.62)	**(4.62)**	**(2.46)**
LIQRISK	0.007	-0.003	0.000	0.000	0.000
	(1.18)	(-1.66)	(0.00)	(-0.01)	(0.83)
CURRENCY	**-0.147*** **	**-0.077*** **	0.005	0.002	-0.006
	(-2.74)	**(-2.93)**	(0.72)	(0.26)	(-0.97)
RETURN VOLA	-0.695	**1.714** **	0.201	**0.263*** **	**0.285*** **
	(-0.49)	**(19.23)**	(1.51)	**(4.88)**	**(3.27)**
ACITIVITY VOLA	**-3.239*** **	**0.663*** **	**0.465*** **	**0.512*** **	**0.497*** **
	(-2.68)	**(3.06)**	**(4.06)**	**(10.66)**	**(5.42)**
Adj. R-squared	0.559	0.597	0.635	0.693	0.680

in the first and third lag (0.262 and 0.275).[43] Hence, at an aggregated level, the excess return of prime brokers displays positive serial correlation rather than mean reversion. This result illustrates that prime brokers are to some degree exercising market power in the short run, as the entire sector is persistently able to generate positive excess returns which are not immediately eliminated by competition. Analogously, the feed-back of the second cointegration equation into the short-run dynamics for hedge funds' illiquidity reconfirms the well-established serial correlation pattern in hedge fund returns (Getmansky et al., 2004).

2.4.2 In the Short Run, Excess Returns on Prime Brokerage and Hedge Fund Illiquidity are Mainly Determined by Asset and Commodity Prices and Perceived Financial Risks.

In the short-run, several contemporary exogenous variables are employed to control for macroeconomic and financial conditions. We find that the trend in house prices (our indicator for asset price bubbles) relates positively to all endogenous variables except for the net securities holdings of prime brokers. Thus, hedge funds in search-for-yield are willing to hold increasingly illiquid real estate-related assets (e.g. junior MBS tranches, CDOs[44]), while prime brokers profit from the financial intermediation involved in the associated securitisation process. Prime brokers nevertheless effectively limit their net exposure to house price trends thereby reconfirming evidence provided by Adrian and Fleming (2005). By contrast, the sizable effect of monthly house price growth on hedge funds' illiquidity premium unveils that hedge funds attempt successfully to profit from short-run price movements as well.

Looking at the other exogenous variables, equity price growth has a negative impact on prime broker excess returns, since a more favourable macroeconomic environment diminishes the relative earnings contribution from prime brokerage given that it raises bank profits and therefore reduces the excess returns of prime brokers. Surges in the prices for gold, oil and foreign exchange decrease the hedge fund illiquidity premium, since the contribution of business activities in the respective liquid markets to hedge fund profits increases. We find the same negative relation for the default risk of corporate bonds. This might reflect that risk-averse investors substitute bonds with other assets thereby pushing up prices and liquidity for the latter and, hence, indirectly lowering the hedge fund illiquidity premium.[45] Supposedly due to growing haircuts and margin

[43] Please note, that we report here the coefficients of the model's VAR representation, which represent the serial correlations in the levels.

[44] A CDO (Collateralised Debt Obligation) is a structured financial product used to repackage and securitise mortgage loans among other things.

[45] We acknowledge the possibility of collinearity issues between the exogenous variables of our model. However, alternatives such as decomposing the exogenous variables' information content by principal component analysis or successive individual orthogonalisation steps would generate information pools which are no longer economically interpretable. Nonetheless, we run additional consistency checks.

requirements (Gorton and Metrick, 2012), prime brokers augment their securities holdings and financing activity when experiencing increases in the default risk.

Finally, as will be discussed in detail in the next subsection, all endogenous variables react to at least one of two variables (RETURN VOLA, ACTIVITY VOLA), each of which represents the risk of entering a high volatility state of either excess returns or of the business activity of prime brokers respectively. Hence, to summarise, the analysis of our control variables confirms that asset prices and risks strongly interfere with the risk premia attached to prime brokerage and hedge funds.

2.4.3 High Levels of Stress in Financial Markets Tend to Weaken the Intermediation Chain, since Prime Brokers Start to Hoard Liquid Securities.

According to Table 2.4, the two variables RETURN VOLA and ACTIVITY VOLA, our measures for the risk of entering financial distress periods, exercise a strong negative effect on prime broker excess returns and a considerable positive influence on hedge fund illiquidity. Thus, investors apparently require higher risk premia for investments in financial intermediaries such as prime brokers or hedge funds during times of exceptional uncertainty.[46] This is consistent with Boyson et al. (2010) who find that extremely negative hedge fund returns cannot be explained by common risk factors. In general, the increase in risk premia reduces the attractiveness of prime brokerage business for banks and burdens hedge funds with the need to generate higher returns on the illiquid, risky part of their business.

Interestingly, the premium on prime brokerage increases much more than the one on hedge fund illiquidity (in absolute terms: 3.239 vs. 2.374). Hence, in times of market stress, market power is shifted from prime brokers to hedge funds. In addition, the effect on prime brokers is driven by the volatility in their business activities, while the one on hedge funds' illiquidity premium is primarily driven by the volatility in the excess return variables (1.714). Hence, more uncertainty about profitability forces hedge funds to offer higher risk premia. Similarly, a volatile pattern of funding liquidity within the financial intermediation chain formed by both types of institutions hurts the excess return of prime brokers. Thus, prime brokers are able to deflect price risks on hedge funds, but need to

Since these checks show that our main findings remain unimpaired and the levels of explained variations remain to a large extent stable, the original model is not exposed to serious collinearity issues. We perform two types of checks. First, we subsequently drop exogenous variables starting from the last variable until the model exclusively comprises the trend in house prices as exogenous variable. In a second step we successively orthogonalise the information contained by the exogenous variables and replace the original variables by their orthogonalised equivalents. In both cases the alternative specifications remain qualitatively identical to the original model with merely few and minor exceptions.

[46] Some readers might be surprised by the notion of investing into prime brokers. Nevertheless, extending a secured loan in form of a repo is comparable to a short-term investment into prime brokers.

accept the major part of the liquidity risks of the joint intermediation chain.

Moreover, when the volatility of excess returns (volatility of prime broker activities) switches to an exceptionally high level, prime brokers' securities holdings and financing activity (all three business activity variables) also rise. Since there is a trade-off between being vulnerable to extraordinary asset withdrawals by hedge fund clients and the exposure to fluctuations of securities prices, the result reflects prime brokers' preference to mitigate the former risk. In other words, prime brokers tend to fend off the risks of runs on their collateral position by increasing their stock of collateral (cf. Singh and Aitken, 2009a; Berrospide, 2012). Hence, in times of market stress, they start hoarding collateral.

These conclusions are corroborated by the dissemination of shocks through the financial intermediation chain. Analysing the consequences of a shock to prime brokers' securities holdings by means of impulse responses (cf. Figure 2.1), we find that an unexpected increase in the risk buffers of prime brokers is highly persistent over time. Simultaneously, the lending and financing volumes of prime brokers decrease for three months. This is also reflected by a short-run reduction of their profits, whereas the liquidity premium of hedge funds persistently rises. Thus, growing risk aversion generates a persistent increase in the risk buffers of prime brokers and reduces their intermediation activity temporarily. Prime brokers are even willing to pay for this risk hedging with a substantial short-run decrease in their excess returns. Hedge funds, on the other hand, are able to exploit the increased demand for illiquid assets or their securitised equivalents used as collateral irrespective of the deleveraging effect generated by the decrease in term lending. They raise their illiquidity premium and are thus able to offer their shareholders an adequate risk premium.

In order to interpret, how this shock disseminates in the system, we perform variance decompositions as a complementary tool. This requires a split-up of the analysis into two cases, because accelerating risk aversion might disseminate through either prime broker lending or financing. We first assume the dominance of prime broker financing over lending in the shock dissemination process (Cholesky order: NETPOS, FINANCING, LENDING, HFILLIQ, PBER). In a second step the emphasis is assigned to the transmission via prime broker lending (Cholesky order: NETPOS, LENDING, FINANCING, HFILLIQ, PBER). Taken together both cases depict the aggregated consequences.

As depicted in Figure 2.4.3, the variance decomposition illustrating the dissemination of a shock to the risk-position via prime broker refinancing is mainly driven by the security holdings of prime brokers and their refinancing volume in repo markets. In detail, the variation of securities holdings is mostly due to serial correlation (roughly 70%). The remainder stems from financing (around 20%) and to a lesser extent from hedge fund illiquidity and lending (both around 5%). Securities holdings of prime brokers explain almost as much variation in prime broker financing than does serial correlation (50%

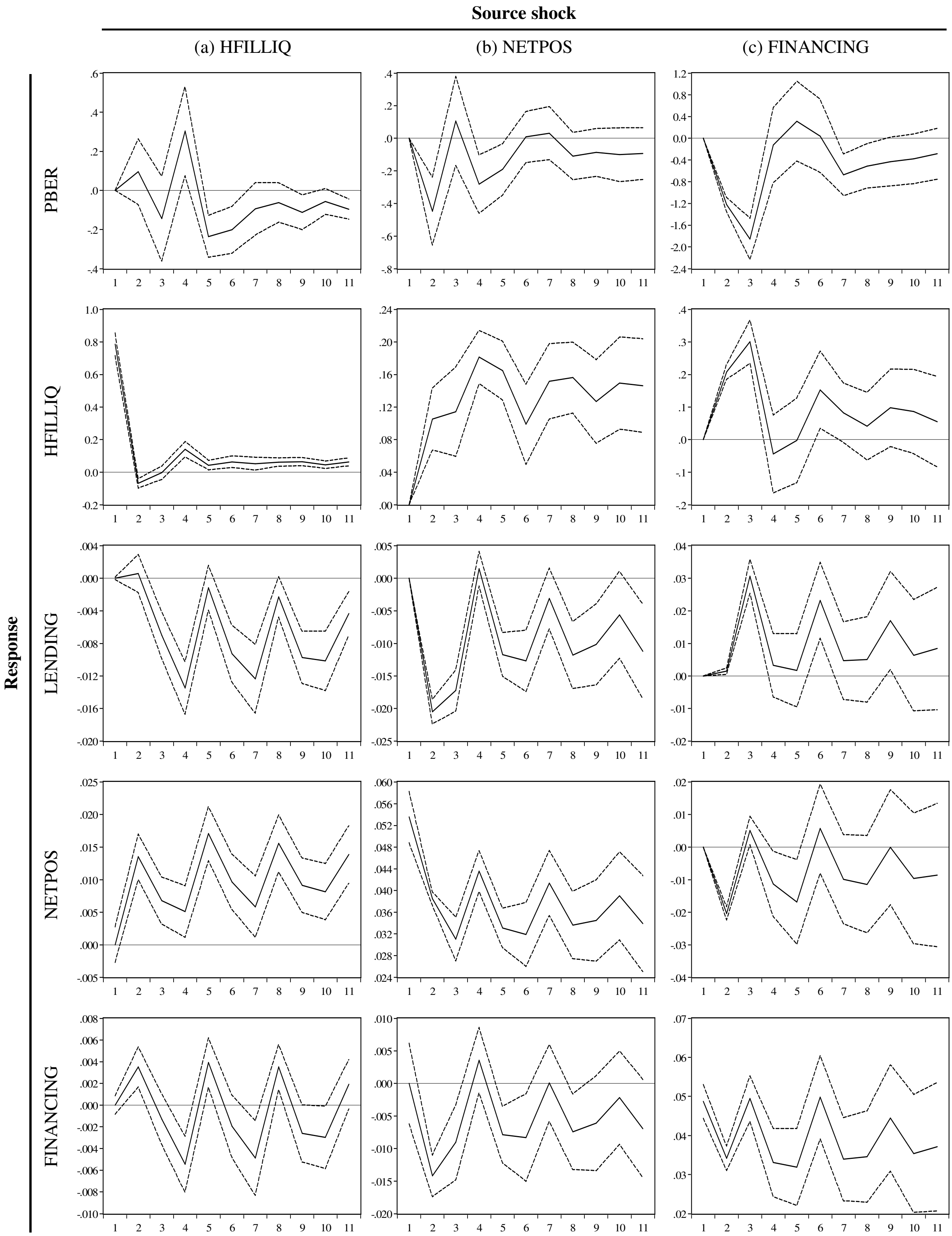


Figure 2.1: Impulse responses. This Figure displays impulse responses of the endogenous variables to shocks in (a) HFILLIQ, (b) NETPOS, (c) FINANCING. Dotted lines denote confidence levels at the 5% significance level. Vertical axes are scaled in Cholesky innovations, horizontal axes are in months.

vs. 40%), while lending activity accounts for the major part of the rest (about 8%). Financing activity picks up most of the variation of prime broker lending (57%) with the remaining variation being almost equally shared by serial correlation and a spill-over from securities holdings (slightly above respectively below 20%). Variation in hedge fund illiquidity rests upon declining serial correlation (90% to 56%) complemented by cross-effects from prime broker securities holdings (up to 23%), prime broker lending and financing (up to 9 and 7% respectively). The excess return of prime brokers results primarily from serial correlation (85%) with the remainder almost entirely due to lending activity (up to 10%).

To the contrary, the variance decomposition illustrating the risk-related shock dissemination via prime broker lending (see Figure 2.3), appears to be mainly driven by prime brokers' securities holdings and lending. The contribution of serial correlation to the variation of securities holdings accounts for roughly 70% with the remainder being mostly due to prime broker lending (around 25%). The variation of prime lending is driven by serial correlation (slightly less than 80%), but reacts also to securities holdings (around 15%). Refinancing operations are hardly serially correlated (20% to 30%). Instead, their variation is mainly generated by securities holdings (around 50%) and lending activity (30% to 20%). The two remaining variables, the excess return of prime brokers and hedge fund illiquidity, are both strongly serially correlated (90% and 90 to 56%), but do also covariate with lending activity (6% respectively up to 17%) and securities holdings (3% respectively up to 23%).

The aggregation of the two effects discussed above reconfirms that the contribution of securities holdings dominates all other cross-effects. This holds in particular for prime broker financing and lending activity. Moreover, the contributions of securities holdings tend to be highly persistent. Thus, the high relevance of securities holdings for the transmission of the shock throughout the system is further reconfirmed.

To summarise, incidents of exceptional uncertainty about the profitability of institutions and/or the volume of business involved in prime brokerage have the potential to prompt sudden interruptions in the associated financial intermediation. Those interruptions are mainly caused by collateral hoarding of prime brokers.

2.4.4 Disruptions in the Financial Intermediation Chain Force Hedge Funds to Deleverage.

For all three cases of shocks associated with risks to the analysed intermediation chain, hedge funds reduce their leverage obtained through borrowing from prime brokers. Those cases include (i) a negative shock to the illiquidity premia of hedge funds associated with an unexpected decrease in the market value of their assets, (ii) an increase of prime brokers' securities holdings, and (iii) a negative shock to prime brokers' financing volume

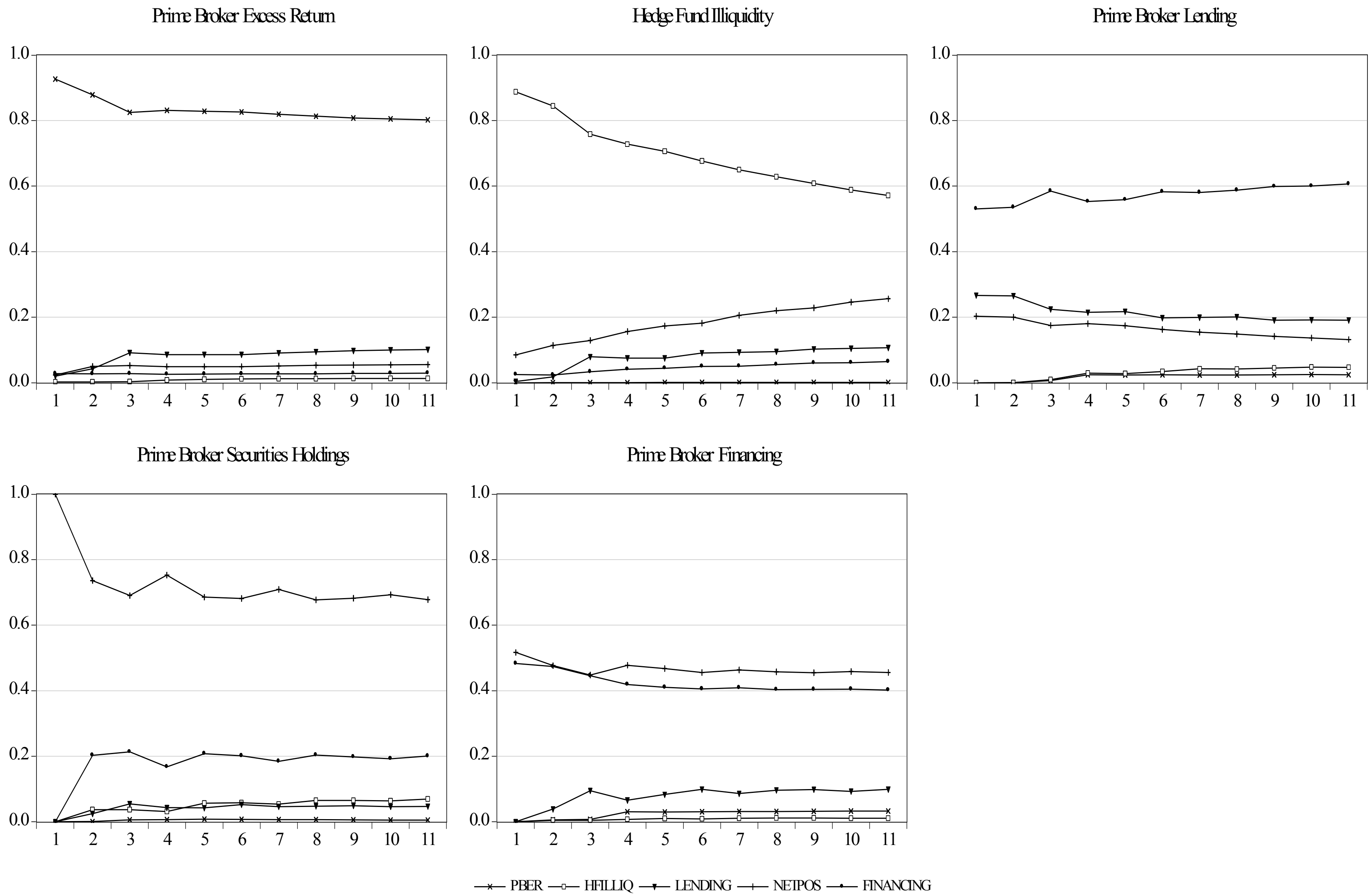


Figure 2.2: Risk shock (prime broker financing). This Figure displays variance decompositions of the endogenous variables. Results are based on Luetkepohl (2005). Cholesky Order: NETPOS, FINANCING, LENDING, HFILLIQ, PBER. Vertical axes are in percentages, horizontal axes are in months.

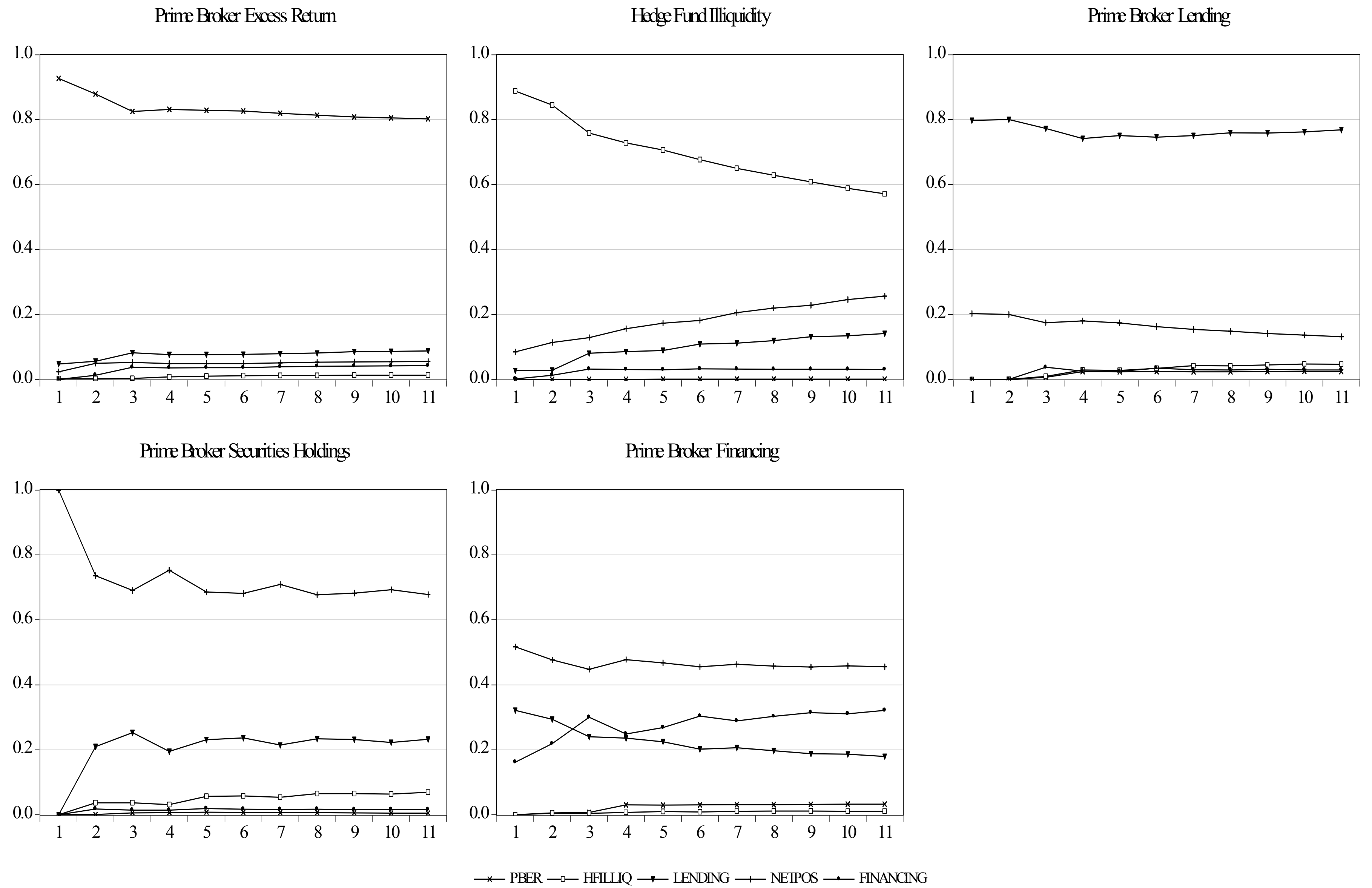


Figure 2.3: Risk shock (prime broker lending). This Figure displays variance decompositions of the endogenous variables. Results are based on Luetkepohl (2005). Cholesky Order: NETPOS, LENDING, FINANCING, HFILLIQ, PBER. Vertical axes are in percentages, horizontal axes are in months.

representing an unexpected decrease of liquidity in repo markets.

The last two shocks generate a temporary reduction in the lending volume of prime brokers and a simultaneous built-up in their securities holdings for up to three months (cf. Figure 2.1), displaying still some persistence afterwards. With lending down and risk buffers up, hedge funds face gradually mounting pressure in rolling over their expiring debt tranches. Hence, they need to deleverage in order to preserve their liquidity positions. As already observed in the previous section, in case of an increase in the risk aversion of prime brokers hedge funds profit from this deleveraging through outright sales of assets to prime brokers, whereas prime brokers are not willing to engage in additional borrowing. On the other hand, hedge funds are forced by shocks to repo markets into a deleveraging process accompanied by decreasing profits. The ambiguity observed in the effects of deleveraging emphasises the importance of the initial shock source: a risk shock benefits hedge funds by generating additional demand for collateral and hence their assets, while a liquidity shock strengthens the position of prime brokers as the intermediary for scarce funding. Thus, as already pointed out before, mounting risks and the incentive to insure against them have the potential to interrupt the particular financial intermediation chain discussed in this paper.

Similarly, a negative shock to the illiquidity premium of hedge funds generates a persistent decrease in the securities holdings of prime brokers as well as negative short-run reactions in both their lending and refinancing activities (cf. Figure **??** and Table 2.4). These effects are driven by a perceived decrease in the value of hedge fund assets. Hedge funds need to deleverage by selling assets, while lower collateral values induce prime brokers to reduce their intermediation activity. However, looking forward to long-run reactions reveals that the negative influence of this rapid devaluation is not persistent, because hedge funds are able to restore their illiquidity premium after a delay of one month almost completely. In response to the valuation shock hedge funds see the opportunity to enter the market again at the now lower level of asset prices. Their demand for additional lending increases. The strong fluctuations observed for this variable indicate that hedge funds continuously receive weakly performing assets back as outstanding collateralised loans expire. Their ability to take on new loans is therefore considerably moderated over longer horizons. Prime brokers, on the other hand, are generally interested in meeting the additional credit demand of hedge funds, and therefore accept new collateral. But these collateral inflows do not suffice to balance the loss in collateral value caused by the initial short-term price decline and the increased haircuts in repo markets. Hence, the refinancing of prime brokers remains flat, even if it displays persistent fluctuations for up to 6 months. Consequently prime brokers meet the increased credit demand of hedge funds only partially; the remaining excess demand resolves through higher funding costs. The profits of prime brokers therefore tend to increase in the long run.

All three effects cause hedge funds to deleverage in reaction to market stress at least in the short run. However, for the case of valuation shocks hedge funds are able to buffer price effects and to reverse the deleveraging in the long run, while adverse shocks on risk perceptions and on repo markets tend to preserve the deleveraging effect due to persistent liquidity hoarding by prime brokers.

Consulting the variance decompositions associated with the different shock types reconfirms the broad picture of the analysis above. For risk shocks to securities holdings of prime brokers, lending is, as already discussed in the previous section, always among the three variables mostly responsible for the transmission through the system (Figures 2.4.3 and 2.3). Similarly, the variance decompositions of a shock to the hedge fund illiquidity premium displayed in Figure 2.4 indicate that lending is among the main drivers for the three business activity variables of prime brokers. In particular, the influence of lending always dominates the contribution to prime brokers' financing activities, while all other variables are to varying degrees dominated by serial correlation.

Regarding negative shocks on hedge funds' illiquidity premium, the variation in the securities position of prime brokers is, besides the dominance of valuation effects through serial correlation, initially influenced by deleveraging. Later on, the illiquidity premium of hedge funds reinforces the serial valuation effect. Both effects reflect the influence of asset or collateral values on the financial intermediation chain from repo markets to hedge funds. More precisely, hedge fund illiquidity starts out completely self-dependent, but over time is also increasingly affected by prime brokers' securities holdings (up to 23%). Prime broker lending looks pretty similar: roughly 90% of total variation is self-explained, with the remainder being pre-eminently driven by prime brokers' securities holdings. By contrast, prime brokers' securities holdings are mainly explained by serial correlation (about 60%) and by hedge fund illiquidity and prime broker lending (both around 20%). Prime brokers' financing activity reacts strongly to lending activity (45% to 70%) as well as to itself and prime brokers' securities holdings (18%). Finally, the variation of prime broker excess returns is primarily due to serial correlation (at least 80%). If at all, prime brokers' securities holdings add some additional explanatory power (roughly 8%). Thus, under the prevalent Cholesky ordering, a shock to hedge funds indeed disseminates mainly via prime broker lending and their securities holdings, whereas their refinancing operations play only a minor role vice-versa.

Finally, for the case of a negative shock to financing, representing periods of squeezed money market funding, prime broker financing dominates the transmission of the shock to all business activity variables (cf. Figure 2.5). Their financing activity is to a considerable degree (around 90%) explained by its own lags, while a minor, if any, cross-effect originates from their lending activity (up to 10%). The majority of the variation of prime brokers' risk position is due to serial correlation (46% to 67%) and prime broker refinancing operations (53% to 19%). A minor effect stems from hedge fund illiquidity (roughly 5%). By contrast, serial covariance contributes only around 20% of the variation of the

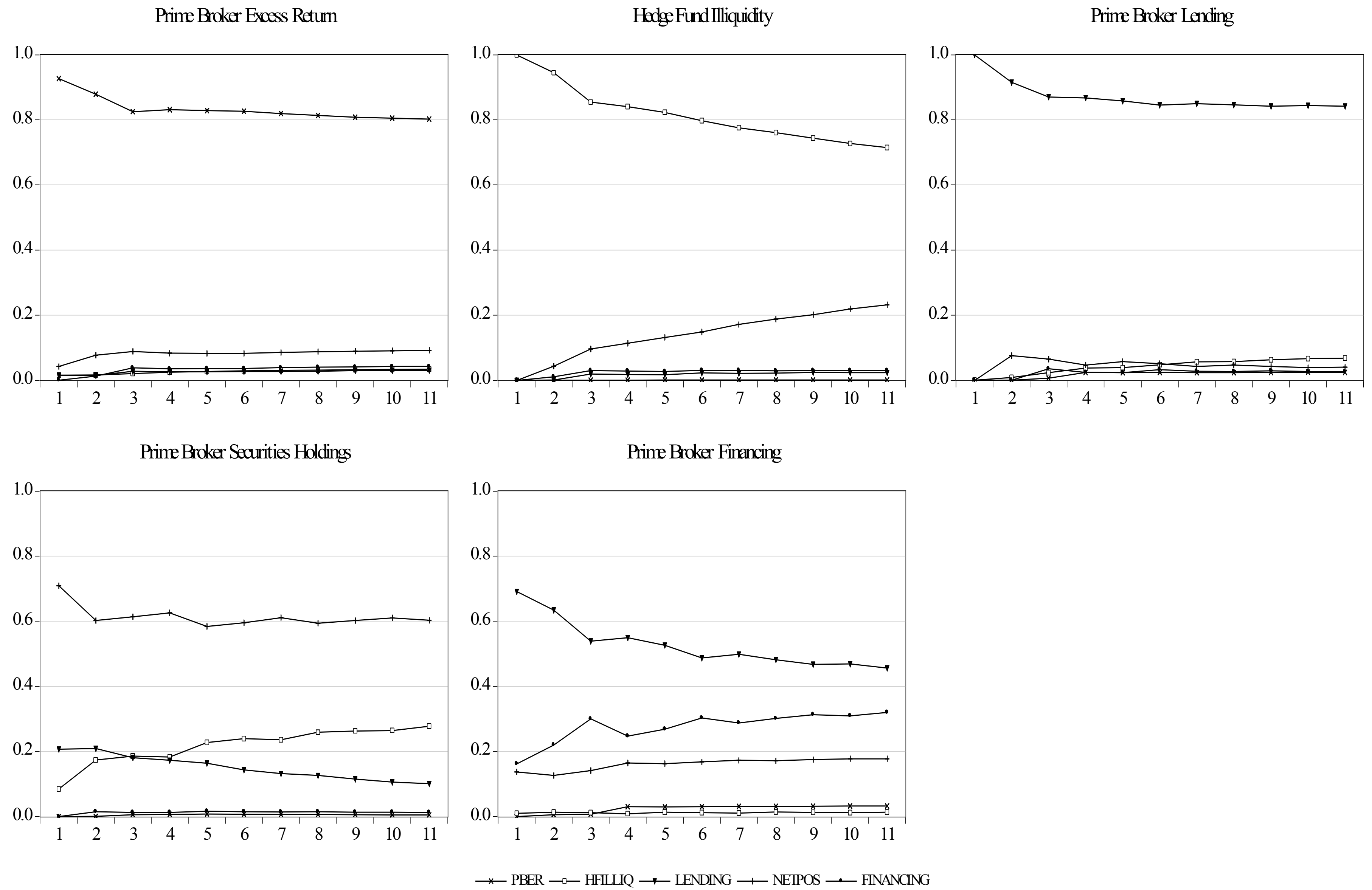


Figure 2.4: Shocks to hedge funds. This Figure displays variance decompositions of the endogenous variables. Results are based on Luetkepohl (2005). Cholesky Order: HFILLIQ, LENDING, NETPOS, FINANCING, PBER. Vertical axes are in percentages, horizontal axes are in months.

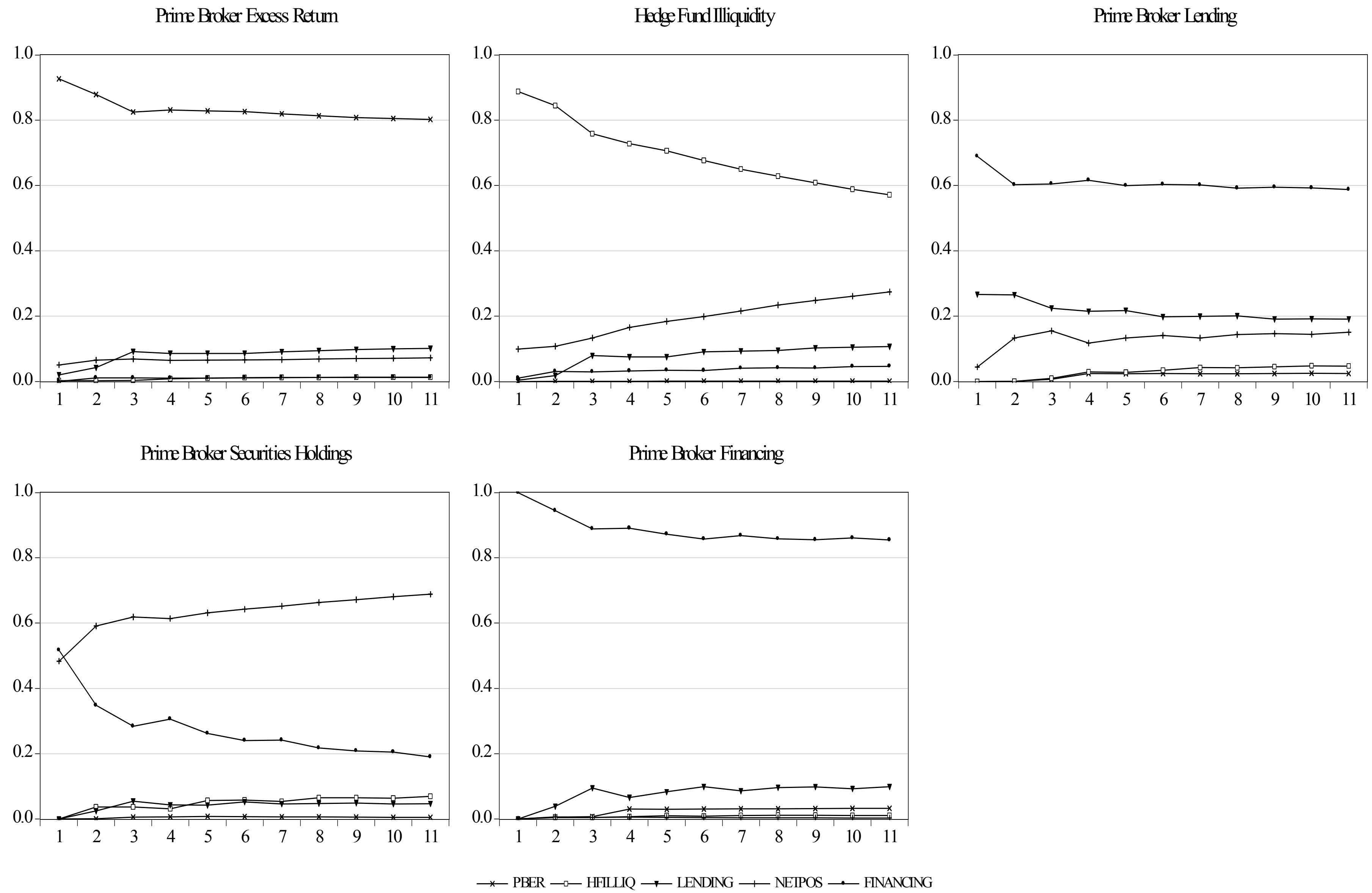


Figure 2.5: Shocks to money markets. This Figure displays variance decompositions of the endogenous variables. Results are based on Luetkepohl (2005). Cholesky Order: FINANCING, NETPOS, LENDING, HFILLIQ, PBER. Vertical axes are in percentages, horizontal axes are in months.

lending activity of prime brokers. Instead, their financing activity (roughly 60%) and securities holdings (about 15%) account for most of the variation.

This dominance of prime brokers' refinancing volume indicates how liquidity in the original funding markets determines the intermediation volume of the entire chain, even if the liquidity squeeze is only partially transmitted to lending behaviour, which is also reflected in a short-term increase of securities holdings within the corresponding impulse responses. This effect also shows up in the prominent cross-effect (up to 30%) of prime brokers' securities holdings on the variation in hedge funds' illiquidity premium. A potential explanation is that the increase in the risk buffers of prime brokers allows hedge funds to couple the deleveraging process with improved margin or haircut conditions. Hence they can hold their illiquidity premium stable. Last, but not least, the excess return of prime brokers results primarily from serial correlation (at least 85%) with the remainder due to lending activity (up to 9%).

To summarise, the presented evidence indicates that adverse shocks to the financial intermediation chain bring hedge funds about to deleverage independent of the original source. However, the dissemination of shocks is strongly source-dependent. The three cases considered above are representative of shocks to hedge fund illiquidity, to the risk position of prime brokers, and to money markets. The dissemination of shocks to hedge funds involves prime broker lending and their risk position, whereas money market shocks spread via prime broker financing and their risk position. A shock to the risk position of prime brokers would on an aggregated level disseminate through all three prime broker activities. Hence, our findings support the notion that different shock sources affect the financial intermediation chain quite differently, even if hedge funds are stimulated to deleverage, at least in the short run, under all shock cases. The implications of this diversity for policy measures are to be discussed in section VI.

2.4.5 Adverse Shocks to any Element of the Intermediation Chain Impair the Profitability of Hedge Funds Stronger than the one of Prime Brokers.

Inspecting the impulse responses to various adverse shock types, we find that shocks to refinancing conditions push up prime broker excess returns and lower the hedge funds illiquidity premium as a result of deleveraging (cf. previous subsection). Vice versa, adverse shocks to the risk buffers of prime brokers raise the illiquidity premium of hedge funds and reduce prime brokers' excess returns. Direct negative shocks to the illiquidity premium of hedge funds are only weakly persistent, but spill also over to the excess returns of prime brokers, even if only to limited degree.

However, further taking into account short-run estimators and variance decompositions, the positive response of hedge funds' illiquidity premium to increasing risks is to a substantial degree driven by a rise in securities holdings and a simultaneous reduction in lending. This has two consequences: on one hand hedge funds experience an increasing rate of return from supplying collateralisable assets. On the other hand, their balance sheets shrink and returns from liquid components of their balance sheet are lost. In total, the risks associated with the entire hedge fund industry increase, since profits depend to a higher degree on successful business with illiquid assets. Thus, investors into hedge funds increase their risk premia. Consequently, the risk-adjusted profits of the hedge fund industry do actually fall rather than increase (cf. Subsection 2.4.3). Hence, hedge funds tend to experience losses in risk-adjusted returns for all shock types. Moreover, comparing the size of the reactions to the standard deviation of the associated residuals reveals that the impulse responses of the hedge fund illiquidity premium always remain below the standard deviation of their own residuals. This does not hold for the reaction of prime brokers' excess returns, which react up to two times the standard deviation of their own residuals.

To sum up, hedge funds tend to suffer from all types of shocks on a moderate level. Prime brokers profit strongly from shocks to financing conditions and weakly from shocks to risk buffers, but suffer from shocks to lending.

2.5 Robustness checks

We employ a number of robustness checks to pre-empt the threat that the model's findings are driven by the model selection procedure, the construction of endogenous variables or omitted variables.

First, we modify the model selection procedure. Instead of focusing on the consistency of different cointegration rank criteria, we examine how modifications to the long-run equations affect the overall model fit and parameter stability. The model fit is measured by the average adjusted R-Squared, while we assess parameter stability based on the absolute value of the percentage change in the significant parameters of the short-run equation (excluding vector error correction). In addition, we use changes in the shock dissemination (impulse responses and variance decomposition) as indirect proxies of parameter stability, since no considerable variations should be found, if parameters remain stable.

As shown in Figure 2.6, the overall model fit peaks when including two cointegration equations with no constants (C2T1) or constants in the long-run part (C2T2). All other specifications fall either considerably below this benchmark or require much more parameters, but fail to improve the model fit. At the same time, parameters seem to be most stable when considering two cointegration equations excluding deterministic trends; an impression further supported by our indirect proxies displayed in Figure 2.7. Furthermore, when comparing the remaining two specifications, we find that the latter yields at least one significant constant. Hence, favouring a relatively lean model specification, our results suggest that the inclusion of a constant in the long-run part constitutes a well-balanced compromise between the model fit and parameter stability. The modified selection procedure accordingly yields results equivalent to those in Section 3.

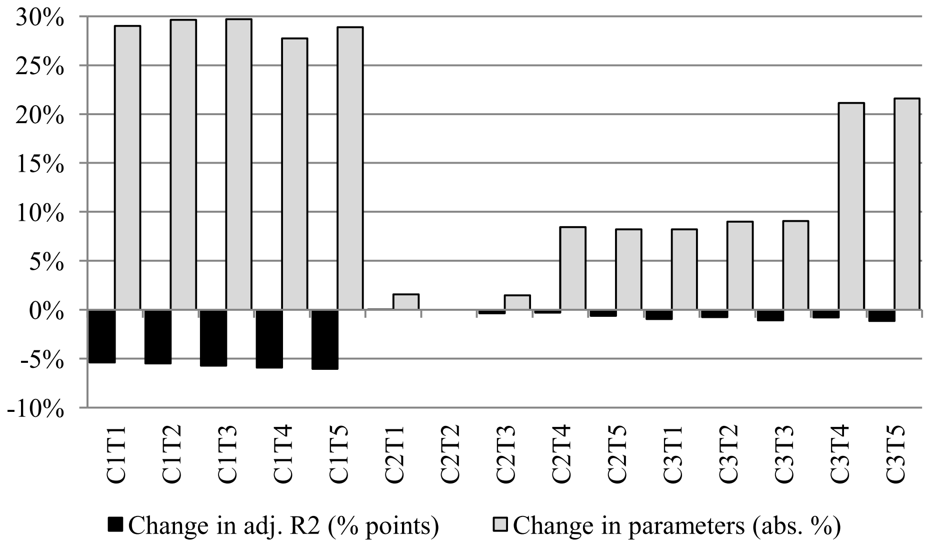


Figure 2.6: Model fit and parameter stability. This figure illustrates deviations in the overall model fit (adjusted R-Squared) and in parameter stability (absolute percentage changes) of various model specifications from the benchmark model (C2T1). Character combinations C1 to C3 represent the number of cointegration equations and character combinations T1 to T5 the inclusion of constants and trends (T1: no constants, no trends; T2: constant in long-run relation; T3: constants in long-run relation and short-run error correction; T4: two constants and linear trend; T5: two constants and quadratic trend).

Second, to evaluate the resilience of the benchmark model, we repeat the analysis of Section 3 using differently constructed endogenous variables and potentially omitted variables. Again, we employ the average model fit and parameter stability as criteria of model robustness. The results are presented in Figure 2.8. We start by applying a narrower set of prime brokersignoring those that do not account for at least 5% of all observed mandates.[47] As a consequence, the average model fit and parameter estimates moderately move (around 12%). Next, we vary the construction of the variable hedge fund illiquidity in several ways: we filter fund-specific returns individually; we include capital inflows into hedge funds as an exogenous factor into the general model; and we include the same variable into the individual as well as the aggregate filtering procedure.[48] All of these modifications do hardly produce any reaction in our two robustness criteria. But the

[47] The total number of prime brokers shrinks to eleven, since we exclude all prime brokers that do not include at least five percent of detected mandates, but include those disappearing during the recent financial crisis (Bear Stearns, Lehman Brothers, Merrill Lynch). Hence, we are left with the following list: Bear Stearns, Deutsche Bank, Credit Suisse, Goldman Sachs, JP Morgan, Lehman Brothers, Merrill Lynch, Morgan Stanley, Newedge (i.e. Credit Agricole, Societe General), SEB, UBS.

[48] Flows into hedge funds are modelled according to Getmansky (2012).

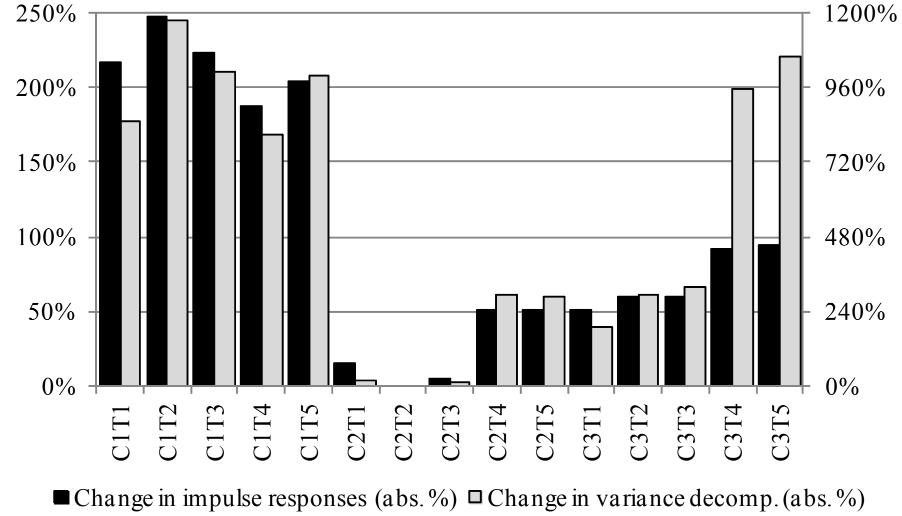


Figure 2.7: Indirect proxies of parameter stability. This figure illustrates deviations in the impulse responses and in the variance decompositions (both 3 lags) of various model specifications from the benchmark model (C2T1). Character combinations C1 to C3 represent the number of cointegration equations and character combinations T1 to T5 the inclusion of constants and trends (T1: no constants, no trends; T2: constant in long-run relation; T3: constants in long-run relation and short-run error correction; T4: two constants and linear trend; T5: two constants and quadratic trend).

same criteria react quite strongly when the Dow Jones Credit Suisse (formerly: Credit Suisse Tremont) and the Hedge Fund Research indices are used as alternative measures for hedge fund profitability. This reflects the higher weight of smaller hedge funds in these two indices. As documented in the methodologies of both indices, the minimum volume of eligible funds is between USD 50 million and USD 100 million by AuM, whereas all of the funds in our sample exceed USD 1 billion AuM. In addition, in case of the Dow Jones Credit Suisse index, eligible hedge funds are not allowed to have investment lockup periods and redemption periods of more than one week. But, especially for large hedge funds, it is common practice to impose significant redemption periods (Fung et al., 2008). Consequently both indices appear much less representative of large and systemically relevant hedge funds, so that the previous conclusions remain unimpaired. If anything, with the model fit remaining decent, the modified model characterises the shock dissemination through the wider hedge fund industry. To conclude, neither the filtering technique, nor taking fund flows into account, nor changing the selection of considered hedge funds undermines the robustness of the benchmark model.

Third, to evaluate whether the model produces consistent empirical results with respect to prime broker activity, we successively replace the overnight and term net financing variables, LENDING and FINANCING, by their net repo equivalents.[49] The latter variables

[49] Similar to overnight (term) net financing, overnight (term) net repo is positive (negative). The interpretation of the alternative proxy for the FINANCING (LENDING) activity of prime brokers

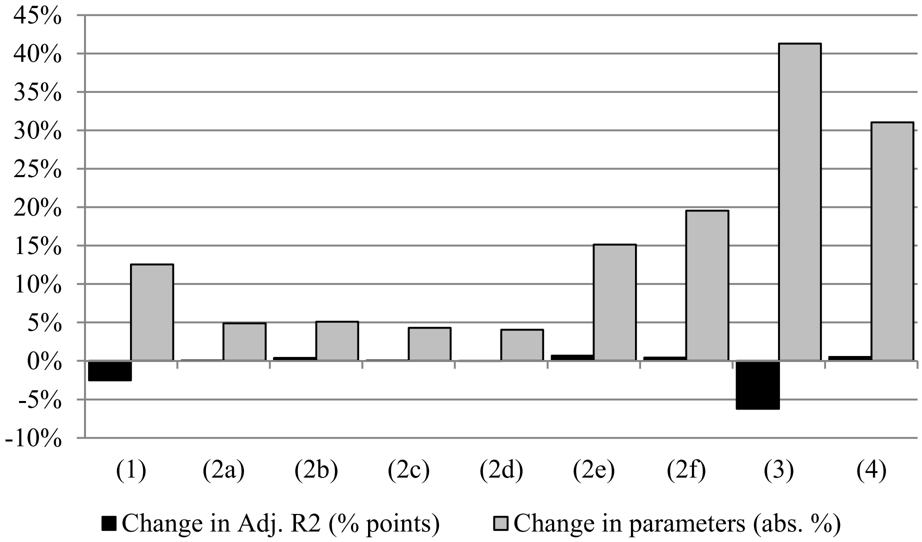


Figure 2.8: Modified variable constructions and omitted variables. This figure illustrates deviations in the overall model fit (adjusted R-Squared) and in parameter stability (absolute percentage changes) of various model specifications from the benchmark model. Specifications differ in modified endogenous variables: (1) prime broker excess return based on narrower definition (weighted by mandates); (2) hedge fund illiquidity based on (a) individual filtering; (b) including fund flows as exogenous factor; (c) including fund flows in individual filtering; (d) including fund flows in aggregated filtering; (e) Credit Suisse Tremont index; (f) Hedge Fund Research index; (3) prime broker lending proxied by term net repo volume; (4) prime broker financing proxied by overnight net repo volume.

follow a narrower definition than net overnight financing or net term financing, because they exclude securities transactions outside of repo—most notably securities borrowing and lending. In this case, overnight repos dominate term repos in terms of volume, since they reportedly constitute one of the most important funding sources for prime brokers. Unsurprisingly, the use of both alternative variables creates considerable shifts in the parameters, though the effect is less elevated for overnight net repo. Thus, the benchmark model continues to provide consistent empirical results.

In a nutshell, our robustness checks reveal that the benchmark model estimated in Section 3 is stable to modifications in the model selection procedure, in the construction of endogenous variables and potentially omitted variables. It turns out that the model is further suitable to even characterise the role of relatively small hedge funds in financial intermediation. Finally, the model derives consistent empirical evidence with respect to a narrower definition of prime broker activity.

is accordingly still ensured.

2.6 The collapse of the financial intermediation via prime brokers and hedge funds during the recent financial crisis

Our findings document that in normal times hedge funds and prime brokers act as complementary trading partners, i.e. hedge funds' illiquidity generates a demand for prime broker lending and thus, with some delay, also the need for a refinancing of prime brokers. This increase in prime broker activity raises their long-run excess profitability, since prime brokers demand compensation for the financial intermediation services provided. Nevertheless, hedge funds benefit as well, since they are able to transform initially illiquid assets into new liquidity. Doing this, they are able to leverage the capital received by the issuance of shares. Since hedge funds invest these additional funds at least partially into illiquid investments, the capital involved finally finds its way into the economy's real sector. However, the finding of a negative short-run feedback of lending on hedge funds' illiquidity indicates that marginal cost effects limit this leverage process in the short run. We also illustrate the outstanding role of hedge funds and prime brokers for the supply of collateral assets to the repo market from an operational point of view. Thereby, we reconfirm the findings of Singh and Aitken (2010). To recapitulate, hedge funds, prime brokers and the repo market together comprise an entire chain of financial intermediation channelling funds from liquid short-term markets into illiquid long-term investments. This particular chain of financial intermediation belongs to the alternatives to traditional banking which are often discussed under the term shadow banking.

Our empirical results demonstrate that this form of financial intermediation has been impaired on the peak of the turmoil generated by the recent financial crisis. We show that, whenever the volatility of prices and business activities switch to extraordinary levels, accelerating securities holdings and financing activity of prime brokers are not accompanied by a rise in lending activity. Hence, we establish that the financial intermediation chain formed by hedge funds and prime brokers is vulnerable. These disruptions are also reflected by higher costs of hedge fund illiquidity and deteriorating prime broker excess returns. Apparently, the drop in financial intermediation affects both the access of hedge funds to liquidity and the need for prime broker services. Hence, we complement the findings of (Klaus and Rzepkowski, 2009) who report a negative influence of a deterioration in the pricing of the associated prime brokers' CDS and implied volatilities on the performance of hedge fund returns which is even more pronounced in the crisis years after 2007, with the difference that our results are based on quantitative information rather than price information.

Furthermore, we find that the impact of a given shock on the intermediation activity of hedge funds and prime brokers strongly depends on its specific source. In particular, a shock to the risk position of prime brokersi.e. fluctuations in their securities holdingstends to have an unusually severe impact on financial intermediation. The reason is that a prime broker's ability to borrow against collateral and to hand out cash loans to hedge funds, in order to receive collateral, weakens at the same time. Thus, the entity subsequently faces an even stronger funding need despite a further impaired access to collateral assets. By contrast, shocks to hedge funds' illiquidity premia or to money market conditions allow prime brokers to adjust either their refinancing activity or their lending activity.

Our results support the notion that precautionary hoarding of liquid securities by prime brokers contributed substantially to this collapse in financial intermediation. Since prime brokers, similar to traditional banks, frequently refinance long-run investments through short-run liabilities such as commercial paper or repos, they are vulnerable to shortages in funding liquidity and runs in a crisis. For instance, rising haircuts might cause a situation where the outstanding repo volume exceeds the collateral value (Martin et al., 2012). In this case, lenders have an incentive to call in on their claims similar to bank depositors. According to Gorton and Metrick (2012), this behaviour has the potential to unfold a run on repo. Moreover, Brunnermeier (2009) argues that startled hedge fund clients might withdraw their liquid wealth held with prime brokers in order to escape negative repercussions for the case that their prime brokers go bankrupt. In analogy to the previous argument, hedge funds would then have an incentive to balance prime broker loans and withdraw pledged collateral. Our evidence is consistent with both explanations. It indicates that prime brokers are aware of the problem and start to raise their liquidity buffers whenever financial turmoil soared: Conditional on exceptional return volatility they increased their securities holdings, but kept lending activity relatively flat, even at the cost of vanishing profitability. Recent studies further substantiate this view. As Singh and Aitken (2009b) point out the hoarding of liquid assets by major banks and prime brokers resulted in a decline of at least USD 5 trillion in globally available liquidity during 2008 alone. In another study, Berrospide (2012) finds corresponding empirical evidence for precautionary hoarding of US commercial banks in anticipation of unrealised losses in their securities portfolios.

Moreover, the empirical evidence delivers plausible explanations for the existence of a common unknown factor in hedge fund returns as well as the collapse in re-hypothecation during the recent financial crisis. Both Billio et al. (2012) and Boyson et al. (2010) document a clustering in hedge fund performance which is unaccounted for by traditional risk factors. Our results suggest that this can be explained by the hoarding of securities by prime brokers which decreases the flow of liquidity to hedge funds and prevents the re-use of eligible collateral assets in repo markets in times of market distress. Hedge funds are therefore left with no choice but to deleverage to remain afloat. According to Ang et al. (2011) hedge funds indeed rapidly reduced their asset holdings and levels of indebtedness in response to the surging financial turmoil in the recent crisis. Thus, the uniformly weak performance among hedge funds during the financial crisis reflects their attempt to sell securities simultaneously.

We corroborate that the sharp decline in re-hypothecation over the recent financial crisis—actual estimates attribute at least USD 1.7 trillion to the largest four global prime brokers (Singh and Aitken, 2009a) and another USD 750 billion to major custodians (Singh and Aitken, 2010)—can also be explained by the detected disruption in financial intermediation. With prime brokers hoarding securities and hedge funds liquidating assets, the debt capacity and thus volume of collateral available to the wider repo market necessarily declined. Consistent with this view Adrian and Shin (2010) find that the actual repo activity (adjusted for M2) of primary dealers' strongly went down on the height of the crisis. Hence, our empirical evidence does not only offer a reasonable explanation for the reduction in re-hypothecation but is also consistent with previous research.

Finally, our results indicate that some of the policy measures implemented by central banks helped to alleviate the disruptions in the financial intermediation chain between hedge funds and prime brokers. In particular, in March 2008 the Federal Reserve Bank of New York created a new facility, the Primary Dealer Credit Facility, which allowed prime brokers in times of market distress a discount-window like access to central bank liquidity. In September 2008, this facility was even enhanced by lowering its collateral eligibility standards (Adrian et al., 2009). The heavy usage of this facility (total of USD 8.95 trillion, thereof USD 1.19 trillion in September 2008 alone) indicates that this specific policy tool fulfilled its purpose to buffer the 2007-2008 liquidity squeeze in repo markets by providing an alternative source of short term funding for prime brokers. In addition, in September 2008 the liquidity swap lines allocated by 15 central banks since late 2007 were also considerably enhanced (USD 830 billion extended in September 2008). Thus, additional liquidity in foreign currency was provided to interbank markets as well.

Both policy measures fall into the time period in which a high concentration of non-zero values in our blip variables indicates the occurrence of financial distress. Therefore, we conclude that our model illustrates some impact of financial distress on the endogenous variables beyond the down-weighing effects of a simultaneous relief by means of policy measures. This finding also reveals that liquidity hoarding by prime brokers was alleviated by the central bank's provision of liquidity. On the other hand, the limited reaction of lending to any shock in prime brokers' financing activity found by our model implies that those policy measures were nevertheless largely effective. Thus, these measures eventually helped to support, among other effects, financial intermediation through hedge funds, prime brokers and repo markets. Hence, the results indicate how crisis-related policy interventions can mitigate the vulnerability of the financial intermediation chain discussed in this paper.

2.7 Conclusions

We analyse the potentially vulnerable and systemically relevant financial intermediation chain established by hedge funds and prime brokers in a heteroskedasticity-robust VEC framework. Our dataset covers the 306 largest global hedge funds and their prime brokers over the period July 2001 to December 2011. The study reveals that in normal times hedge funds and prime brokers act as complementary trading partners. Their interconnected business is mainly driven by asset prices and the risks perceived in relevant markets.

However, we provide empirical evidence that this specific form of financial intermediation was substantially reduced at the height of the recent global financial crisis. Our results suggest that this break-down was due to the hoarding of liquid securities by prime brokers being eager to avert runs by their clients. The trigger behind this behaviour was an increase in the observed volatility of market activities reflecting a general increase in perceived risks. Hence, our findings are consistent with previous evidence on the behaviour of prime brokers (Singh and Aitken, 2009a) and commercial banks (Berrospide, 2012) during the crisis.

Beyond that, we provide fresh insights into the distinct dynamic dissemination pattern of financial shocks through hedge fund illiquidity and prime broker activity. First, we demonstrate that all adverse shocks which could in some form be observed during the recent financial crisis induce hedge funds to deleverage. Second, the deleveraging process impairs the profitability of hedge funds stronger than the one of prime brokers. Third, the consequences of a particular shock strongly depend on the respective source, whereas prime brokers' securities holdings play in any event a central role in the shock transmission.

From a systemic risk perspective, our results emphasise the fact that fairly general shocks to markets can severely impair one of the potential substitutes for the traditional financial intermediation chain through banking. Moreover, the central factor in these reactions is the securities hoarding by prime brokers. Since prime brokers are closely connected with the traditional banking system, feed-back effects towards commercial banks are highly probable. In addition, the central role of prime brokers' securities holdings indicate that prime brokers are systematically relevant by nature, since they form the central node in transmitting shock events throughout the entire intermediation chain—apart from the pure fact that this market segment is anyway highly concentrated. This is why we find, that central bank interventions on the height of the recent crisis appear to have substantially cushioned the negative effects of financial meltdown on collateral-based financial intermediation in general.

Several robustness checksvariations in the construction of endogenous variables, a modified model selection procedure, inclusion of potentially omitted variablesreconfirm that the estimated heteroskedasticity-robust VEC model eventually provides a sound description of the financial intermediation chain established by hedge funds and prime brokers. Building on this stable structure, future revisions, e.g. the use of a panel data framework, have the potential to deliver results which reflect also the heterogeneity of the hedge fund industry. Most notably, such an extension could be useful to explore the transmission of effects within the hedge fund sector. In such a way, it could be even possible to identify those funds which are systemically relevant due to characteristics beyond their pure size properties.

Chapter 3

Two Sides of the Same Coin? Financial Integration vs. Financial Contagion

This chapter is joint work with Steffen Sebastian.

Abstract

Global financial integration benefits financial institutions in normal times, but makes them vulnerable in turbulent times. This paper explores the financial integration of 21 developed countries during the Subprime Crisis and the Euro Crisis, using their financial sector co-movement as a proxy. A novel Factor DCCX model allows us to examine the drivers of financial sector co-movement, while accounting for spillovers from securities markets, crisis-related regime-shifts and heteroskedasticity. The empirical evidence indicates that the Subprime Crisis was a global event propagated by US and global contagion following the crash of Lehman Brothers. However, the Euro Crisis was a regional event marked by a US-driven decoupling of the countries at the centre of investor concerns.

3.1 Introduction

This study examines the development of global financial integration between 2001 and 2012 and the impact of the global financial crisis of 2007-09 (Subprime Crisis) and the as yet unresolved European sovereign debt crisis (Euro Crisis) on its progress. The crisis aspect is particularly interesting since markets frequently "overreact" to negative shocks elsewhere in episodes of financial turbulence. Economists often call this phenomenon "contagion". The common definition that we adopt describes "contagion" as financial sector co-movement in excess of what is justified by fundamentals.[50] Depending on the geographical source, we further differentiate "US contagion", "global contagion" and "domestic contagion". On the other hand, excessive disintegration of financial sectors vis-à-vis the US is labelled "flight-to-quality" as it results from investors unilaterally relocating investments from the periphery to "safe havens".

In normal times, a high degree of integration between a domestic financial sector and its US equivalent—the centre of today's global financial system—is a key criterion to attract funds from investors. Strong financial sector integration ensures that domestic financial institutions benefit from both a broad range of products (i.e. market width) and a high investment volume per asset class (i.e. market depth). Besides, international investors may easily move their investments across borders. However, in the presence of financial stress shocks may also quickly spread from one financial sector to the next. This is why the degree to which a given financial sector connects to the US financial system constitutes a solid proxy not only of financial integration during tranquil periods, but also for its vulnerability during periods of turmoil.

Acknowledging the dominant role of the US financial sector, we therefore measure financial market integration by the financial sector correlation of 19 developed countries vis-à-vis their US equivalent.[51] Correlations are determined based on a two-stage Factor DCCX model in the spirit of Engle (2009). The first-stage estimation builds on the three-factor asset pricing model of Bekaert et al. (2014). The three factors account for US-specific, global financial and domestic shocks. The financial sector performance may further respond to crisis-related regime shifts and investor expectations. Next, we screen the first-stage residuals for the remaining uncovered co-movement using an extended version of Engle's (2002) dynamic conditional correlation approach. The correlation structure incorporates extreme US-specific and domestic news shocks as well as tensions in international securities markets. In the last step, we reassemble the different correlation components to characterise the aggregate financial sector co-movement and to identify its sources.

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[50] Cf. Eichengreen et al. (1996); Bekaert et al. (2005); Bekaert et al. (2014).

[51] If two markets display a high level of co-movement, they are well integrated because investors treat both markets fairly similarly.

The Factor DCCX model provides a number of advantages. First, the three-factor model establishes an understanding of the standard shock transmission against which periods of financial disorder can be benchmarked. Second, the DCCX-implied residual correlation dynamics help us to determine how acute financial stress interferes with financial sector integration in the short term. Third, our approach does not suffer from the heteroskedasticity bias described by Forbes and Rigobon (2002) since all the inherent variance processes are dynamised to reflect financial sector co-movement adequately. Hence, our approach facilitates the undisturbed detection of even excessive correlation movements and their sources.

Overall, our results show a high degree of financial integration across countries; however, it is strongly impeded by contagion and flight-to-quality during episodes of financial stress. For instance, contagion spread financial turmoil to most countries examined following the crash of the investment bank Lehman Brothers in the Subprime Crisis. Its average size was 16.3% of unconditional correlations. By contrast, the countries at the centre of the Euro Crisis (Greece, Italy, Portugal, Spain) showed remarkable decoupling from the US financial sector (-20.1% of unconditional correlations), which even accelerated over the course of the crisis (from -19.3% to -28.8%). Since spillovers towards other financial sectors became increasingly unlikely in the latter case, financial stress remained widely incarcerated in the four crisis countries. The Euro Crisis wss therefore essentially a regional event, as opposed to the global scope of the Subprime Crisis.

A closer look at what lies behind contagion and flight-to-quality further reveals that the US component was the primary source of excessive co-movement during both crises. It boosted the interconnectedness of domestic financial sectors during the Subprime Crisis and prompted the decoupling of the worst-hit countries in the Euro Crisis. By contrast, the domestic and residual components had a consistently abating effect on financial sector co-movement. Thus, the two alleviated the extent of contagion (from 13.3% to 7.5%), but reinforced flight-to-quality (from -15.2% to -20.1%). The global component merely played a less prominent role.

These findings have far-reaching implications. First, interventions of US policy makers have the largest potential to counteract global financial crises due to the observed dominance of the US component in the shock transmission. Second, domestic policy makers may nonetheless help to isolate financial turmoil given the considerable negative impact of the domestic and residual component on correlations. This is corroborated by the fact that residual co-movement was particularly negative following peaks in financial stress, and thus precisely when governments and central banks most actively intervened in financial markets. Such measures included government bailouts and massive central bank liquidity injections.[52] Third, the negative contribution may by itself create new chal-

[52] A good overview of policy interventions is provided by the St. Louis Federal Reserve Bank's Crisis Timeline: http://timeline.stlouisfed.org/index.cfm?p=timeline#.

lenges for domestic policy makers in the presence of a regional crisis, because it reinforces excessive capital withdrawals to "safe havens". This is all the more problematic in the special case of the Euro Crisis, since flight-to-quality compromises the homogeneity of the financial sectors within the euro area. As a result, the effectiveness of the monetary policy may suffer and the vulnerability of the crisis countries' domestic economies may increase. Fourth, the proposed Factor DCCX model is particularly suited to modelling macro-financial risk scenarios, due to the fact that it improves the correlation estimates when they are needed the most for risk management purposes, such as hedging activities or value-at-risk calculations.

Our study contributes to the literature on financial crises in two ways. First, it adds fresh insights regarding the global propagation of financial stress *across financial sectors* in the Subprime Crisis and the Euro Crisis. Several studies have pointed out that the stability of financial institutions during the Subprime Crisis rested upon their exposure to the US MBS market (cf. Allen and Carletti, 2008; Acharya and Schnabl, 2010; Kacperczyk and Schnabl, 2010) and secured money markets (cf. Gorton and Metrick, 2012; Longstaff, 2010; Martin et al., 2012; Taylor and Williams, 2009). Eichengreen et al. (2009) further identified common factors as major drivers escalating bank counterparty risk. In a financial network framework, Glasserman and Young (2014) concluded that highly leveraged financial institutions dependent on interbank funding trigger the fiercest spillovers. On the other hand, the growing research on the Euro Crisis, though mostly concentrating on sovereign bond markets, confirms that the crisis made troubled countries drift apart: Chudik and Fratzscher (2013) observed "a flight-to-safety phenomenon across asset classes", which particularly punished the yields of peripheral countries with weak fundamentals.[53] Besides, local factors became the dominant determinants of the sovereign CDS spreads of the crisis countries (cf. Beirne and Fratzscher, 2013; De Santis, 2012). Finally, Black et al. (2013) showed that when the systemic risk of European banks peaked in 2011, the risk contribution of Italian and Spanish banks also reached its highest point.

Second, we propose a new heteroskedasticity-robust framework to quantify the propagation of financial stress. The work of Bekaert et al. (2014) and Engle (2009) is probably closest to ours. Engle (2009) proposed a two-step estimation of equity correlations combining factor asset-pricing models and DCC models, but ignored crisis-related dynamics. Bekaert et al. (2014) studied regime shifts in a sophisticated factor asset pricing model, yet did not explicitly take into account the exuberant and short-lived correlation dynamics typical of periods of stress.[54] Moreover, Chiang et al. (2007) and Forbes and Rigobon (2002) investigated the shifts in correlation dynamics to reveal incidents and sources of contagion.

[53] Evidence of a flight-to-safety phenomenon in European bond markets can already be found in the pre-euro era during the Russian debt crisis or the LTCM incident (Beber et al., 2008).

[54] Related factor asset pricing models include Bekaert et al. (2005) and Engle et al. (1992).

The rest of the paper proceeds as follows. The next section describes our data set. Section 3.3 outlines the two-stage Factor DCCX model. The empirical results are presented in Section 3.4 as well as a decomposition of the heteroskedasticity-adjusted overall correlations in its sources. Finally, Section 3.5 concludes and discusses the implications of our empirical findings for systemic risk and risk management.

3.2 Data

This study uses midweekly equity, interest rate and repo market data between 4 July 2001 and 26 September 2012. This choice allows for the highest possible frequency whilst sidestepping potential temporal inconsistencies.[55] All the variables are measured in US dollars (USD).[56] If not otherwise indicated, the entire data set originates from Thomson Reuters Datastream.[57]

The MSCI Country and MSCI Financials total return indices serve as our measures of overall and sector-specific equity market performance. We cover 20 major developed countries from four regions: Asia/Pacific (Australia, Japan, Hong Kong), the euro area (Austria, Belgium, Finland, France, Germany, Greece, Italy, the Netherlands, Portugal, Spain), non-euro European countries (Denmark, Norway, Sweden, Switzerland, the UK) and North America (Canada, the United States). We further collect each financial sector's weekly dividend yield as an indicator of its profit situation and LIBOR with the same maturity as a proxy for opportunity costs. Finally, we compile the total number of failed repo settlements (i.e. "fails to deliver" plus "fails to receive") from the Federal Reserve Bank of New York's primary dealer database as a measure of disruptions in securities markets.

The study applies four types of variables. The first category includes the dependent variables. These are the excess returns of the financial sector in country i during week t (R_{it}) defined as the financial industry-specific stock return over the corresponding LIBOR rate with the same tenor. The second category features a US factor (f_t^{US}), a global financial factor (f_t^G) and a domestic factor (f_{it}^D) used as exogenous variables. The US factor equals the MSCI USA total return. The global financial factor is the residual of a regression of the MSCI World Financials total return on the US factor. In the same manner, a country's domestic factor is computed as the residual from a regression of the

55 Varying time zones and weekends may harm the interpretability of studies with a global focus, as newly arriving information affects some markets during trading hours, when other markets are closed. For more detailed discussions on this topic, please refer to Chiang et al. (2007) and Forbes and Rigobon (2002). One approach (the one employed here) tackling this issue is to make explicit use of midweek data.

56 We also performed the analysis using returns, dividend yields and interbank offered rates denominated in local currency. The results remained qualitatively unchanged.

57 For details of the variables and sources, see Table C.1 in the appendix.

local MSCI total return on the two other factors. This procedure safeguards potential endogeneity issues.[58] The third category covers two regime dummies. The first dummy (CR_1) spans the Subprime Crisis from the onset of global money market stress in early August 2007 to the trough of global stock markets in March 2009. The second dummy (CR_2) accounts for the Euro Crisis between October 2009 and the end of September 2012.[59] The fourth category reflects the state of collateral-based financial intermediation. Our measure is the *unexpected* portion of the total number of failed repo settlements (i.e. "fails to deliver" plus "fails to receive") involving government and corporate bonds. Since repos link the secured money market to a variety of asset markets by construction, settlement failures are generally a solid indicator of counterparty risk and asset price volatility. The unexpected portion of failed repo transactions, y_t, is the residual after controlling for a constant and serial correlation of order one. Table C.2 in the appendix exhibits descriptive statistics of the respective variables.

3.3 Modelling Financial Sector Co-movement

In the style of Engle (2009), we determine the co-movement of the US financial sector with that of other developed countries during the Subprime Crisis and Euro Crisis. This approach reflects that the US are the centre of the global financial system. Accordingly, any change in the correlation vis-a-vis the US merely illustrates an alteration in the degree of a country's integration into the global financial landscape. Therefore, it is arguably even possible to draw inferences from the co-movement with the US financial sector about a country's financial integration with third countries.[60] This property will be particularly useful when investigating the Euro Crisis.

The analysis proceeds in three steps. The first step estimates a three-factor asset pricing model to single out common shocks (cf. Bekaert et al., 2014). The second step identifies residual correlation patterns using an extended version of Engle's (2002) DCC model, which includes exogenous variables. The third step assembles the aggregate correlation from its components. We call this approach a Factor DCCX model.

The Factor DCCX model provides several advantages. First, the three-factor model establishes an understanding of the standard shock transmission against which periods of financial disorder can be benchmarked (cf. Bekaert et al., 2014). Second, the residual correlation dynamics help us to ascertain how acute financial stress interferes with financial sector integration in the short term. Third, our approach does not suffer from

58 The orthogonalization procedure yields very similar results when crisis dummies are included

59 The two crisis definitions are consistent with Bekaert et al. (2014) and (Lane, 2012), respectively.

60 Please keep in mind that correlations just mirror the underlying dynamics. In fact, we construct correlations from a three-factor model. Thus, if a given country's correlations vis-a-vis the US stand out, this is because the country responds differently to the underlying factor than other countries do (including the US).

the heteroskedasticity bias described by Forbes and Rigobon (2002) as all the inherent variance processes are dynamised to reflect the financial sector co-movement adequately. Hence, our approach facilitates the undisturbed detection of even excessive correlation movements and its sources (cf. Engle, 2009).

3.3.1 The Three-Factor Asset Pricing Model

The first step applies the three-factor asset pricing model of Bekaert et al. (2014) to the excess return, ER_{it}, of a given domestic financial sector:

$$ER_{it} = E_{t-1}[ER_{it}] + \beta_i^{'} F_t + \gamma_i^{'} CR_1 F_t + \eta_i^{'} CR_2 F_t + \lambda_i CR_1 + \tau_i CR_2 + \epsilon_{it}, \tag{3.1}$$

$$E_{t-1}[ER_{it}] = \kappa_i R_{it-1} + \psi_i DY_{it}, \tag{3.2}$$

$$\epsilon_{it} | I_{t-1} \sim N(0, h_{it}). \tag{3.3}$$

The vector $F_t^{'} = [f_{it}^D, f_t^G, f_t^{US}]$ contains a domestic, global financial and US factor. Two regime variables, CR_1 and CR_2, capture crisis-related asymmetries. The expectations of the current excess return, $E_{t-1}[ER_{it}]$, are a linear function of the lagged excess return and the local dividend yield, DY_{it}. The vectors $\beta_i^{'} = [\beta_i^D, \beta_i^G, \beta_i^U S]$, $\gamma_i^{'} = [\gamma_i^D, \gamma_i^G, \gamma_i^U S]$ and $\eta_i^{'} = [\eta_i^D, \eta_i^G, \eta_i^U S]$ contain factor loadings depending on the present regime. λ_i and τ_i are parameters. The residual ϵ_{it} denotes a domestic financial sector shock with mean zero and time-dependent variance, h_{it}. I_{t-1} includes all the information available up to and including week $t-1$.

In the special case of the US financial sector ($i = 0$), the domestic and US factors coincide. The above model therefore reduces to a two-factor model, which is incapable of identifying systematic co-movement with the other domestic factors. We propose the following auxiliary regressions for each country to overcome this shortcoming:

$$\epsilon_{0t} = \big(\beta_i + \gamma_i CR_1 + \eta_i CR_2\big) f_{it}^D + u_{it}. \qquad i \neq 0 \tag{3.4}$$

The error term u_{it} ($i \neq 0$) is the portion of the US financial sector excess return independent of country i's domestic factor.

Bekaert et al. (2014) remarked on the following. First, a comparable three-factor asset pricing model may nest three different CAPMs: given that all the other parameters are zero, the model converges to a domestic ($\beta_i^D > 0$), global financial ($\beta_i^G > 0$) or US ($\beta_i^{US} > 0$) CAPM. Second, the model allows us to study crisis-related asymmetries in excess returns and their sources. If a slope parameter in the vector $\gamma_i^{'}$ or $\eta_i^{'}$ is significantly positive (negative), this is evidence of "contagion" ("flight to quality") since the beta coefficients systematically underestimate (overestimate) the reaction of financial sector performance to common shocks. An analogous rationale applies to the parameters λ_i

and τ_i. By contrast, in the absence of crisis-induced asymmetries, the authors referred to "interdependence". Third, the correlations between any two countries increase in the three factors provided that the excess return expectations are idiosyncratic. Thus, the asymmetries identified in excess returns also persist in correlations.

3.3.2 The Dynamic Conditional Correlation Model

The second step screens the first-stage residuals for as yet unaccounted for residual co-movement. Since the above asset pricing model removes most information attributable to common shocks, regime shifts and serial correlation, any remaining systematic co-dependence is likely to be related to extreme events or spillovers from other financial markets. Such incidents typically materialise during periods of financial stress. In order to take care of these features, we modify Engle's (2002) original dynamic correlation structure by including asymmetries and exogenous variables.

The starting point of our illustration is his original bivariate DCC approach (Engle, 2002). As he described, we initially form $i-1$ pairs of residual excess returns, $\varepsilon_{it}^{'} = [u_{it}, \epsilon_{it}],\ i \neq 0$. In a move to simplify the notation, the residuals are relabelled: $\varepsilon_{1t} = u_{it}$ and $\varepsilon_{2t} = \epsilon_{it}$. This alteration allows us to prevent the illustration from becoming unnecessarily complex.

The time-varying covariance matrix of a given pair of residuals is:

$$H_t = D_t R_t D_t, \tag{3.5}$$

where $D_t = diag(\sqrt{h_{1t}, h_{2t}})$ is a 2×2 diagonal matrix of conditional standard deviations. The variances themselves are assumed to follow univariate GARCH(1,1) processes,

$$h_{jt} = \omega_j + \delta_j \epsilon_{jt-1}^2 + \theta_j h_{jt-1}^2, \qquad j = 1, 2 \tag{3.6}$$

with parameters ω_j, δ_j and θ_j.[61] Besides, $R_t = (diag[Q_t])^{-1} Q_t (diag[Q_t])^{-1}$ is the 2×2 time-varying correlation matrix of standardised residuals, $\xi_t^{'} = [\xi_{1t}, \xi_{2t}]$, with a typical matrix element ρ_{12t}^R. The standardised residuals are formed by dividing the respective residual excess return by its standard deviation, $\xi_{jt} = \varepsilon_{jt}/\sqrt{h_{jt}}$ $(j = 1, 2)$. The covariance matrix, Q_t, of the standardised residuals takes the form of a quadratic 2×2 matrix. Its elements, q_{11t}, q_{12t} and q_{22t}, are used to determine the conditional residual correlation, $\rho_{12t} = q_{12t}/(q_{11t} q_{22t})$. The DCC model applies the following correlation structure:

$$q_{12t} = \rho_{12}(1 - \alpha - \beta) + \alpha \xi_{1t-1} \xi_{2t-1} + \beta q_{12t-1}, \tag{3.7}$$

[61] We also experimented with asymmetric effects in the conditional variance process as proposed by Glosten et al. (1993) and Zakoian (1994). However, the inclusion of an additional parameter hardly contributed to the variances.

where ρ_{12} denotes the unconditional correlation of standardised residuals. The parameters α and β are estimated subject to the constraint $1 - \alpha - \beta > 0$. Please note that the parameter β is chosen in accordance with the notation in Engle (2002), but differs from the β coefficient in the three-factor asset pricing model.

As mentioned earlier, we propose the following augmented DCCX correlation structure to examine the impact of extreme events and spillovers on residual co-movement:

$$\begin{aligned} q_{12t} &= DCC_{12t} + (\phi_1 XTRM_{1t-1} + \phi_2 XTRM_{2t-1})\xi_{1t-1}\xi_{2t-1} + \phi_3 y_{t-1}, \\ DCC_{12t} &= \rho_{12}(1 - \alpha - \beta) + \alpha\xi_{1t-1}\xi_{2t-1} + \beta q_{12t-1}. \end{aligned} \tag{3.8}$$

The two variables $XTRM_{jt}$, $j = 1, 2$, identify unexpected domestic news shocks. Each identifier indicates whether the absolute value of the residual ϵ_{jt} in country $j = 1, 2$ falls into the highest 2.5 percentile.[62] The variable y_t controls for spillovers from repo market failures.[63] The term DCC_{12t} stands for the original bivariate correlation structure. ϕ_1, ϕ_2 and ϕ_3 are parameters.

There is no systematic co-movement in the residual excess returns if all the parameters in Equations 3.7 and 3.8 are insignificant. Otherwise, the first-stage asset pricing model miscalculates the actual dependence between financial sectors. Then, the estimated coefficients ϕ_1, ϕ_2 and ϕ_3 report the existence and type of systematic co-movement in the residual excess returns. First, if all the parameters ϕ_1, ϕ_2 and ϕ_3 in equation 3.8 are zero, the correlation structure corresponds to the DCC model (Engle, 2002). Second, dramatic news has a positive (negative) asymmetric impact on conditional correlations, if $\phi_1, \phi_2 > 0$ ($\phi_1, \phi_2 < 0$). In the case that the parameters point in opposite directions, simultaneously appearing domestic news shocks may partly offset one another. The actual bearing on residual correlations then rests upon the intensity of the signals. Eventually, a significant coefficient, ϕ_3, implies a spillover from repo market failures onto the residual financial sector co-movement. If the parameter is positive, unexpected repo failures translate into higher residual correlations.[64]

The two-step estimation proceeds as in Engle and Sheppard (2001). The parameters of

[62] By selecting events based on the absolute value of the first-stage residual, we let the data generating process decide whether positive or negative domestic news shocks are considered. The imposed threshold (2.5 percentile) ensures that extreme events are limited to one event in five months or about 5% of all weeks.

[63] The ideal risk proxy oscillates with mean zero, but may briefly cluster during periods of financial stress. Unexpected repo failures satisfy these requirements.

[64] Under certain conditions, the marginal effect of a change in the exogenous variable can be reversed. A detailed analytical derivation of this issue is presented in the appendix. As the empirical results show, the issue is mostly negligible, since it emerges in merely 10 out of 11,134 weekly observations ($\simeq 0.09\%$).

the GARCH(1,1) process are determined in the first stage:

$$LLF_1 = -\frac{1}{2}\sum_{t-1}^{2}\left[Tlog(2\pi) + \sum_{t-1}^{T}\left(log(h_{jt}) + \frac{\epsilon_{jt}^2}{h_{jt}}\right)\right], \qquad j = 1, 2, \tag{3.9}$$

and those of the DCCX model in the second stage:

$$LLF_2 = -\frac{1}{2}\sum_{t-1}^{T}\left[2log(2\pi) + 2log|D_t| + log(|R_t|) + \xi_{t-1}^{'}R_t^{-1}\xi_{t-1}\right]. \tag{3.10}$$

3.3.3 Correlation Components

The third step assembles the aggregate correlation based on its components to characterise financial sector co-movement accurately over time. According to standard statistics, the correlation coefficient in week t between the US financial sector ($i = 0$) and any other country ($i \neq 0$) is defined as their covariance, $Cov(ER_{0t}, ER_{it})$, divided by the square root of their variances, $V(ER_{0t})$ and $V(ER_{it})$:

$$\rho_{0it} = \frac{Cov_t(ER_{0t}, ER_{it})}{\sqrt{V_t(ER_{0t})V_t(ER_{it})}} = \frac{C_{0it}^D + C_{0it}^G + C_{0it}^{US} + C_{0it}^E + C_{0it}^R}{\sqrt{V_t(ER_{0t})V_t(ER_{it})}}, \qquad i \neq 0. \tag{3.11}$$

The covariance is composed of a domestic component, C_{0it}^D, global component, C_{0it}^G, US component, C_{0it}^{US}, expectations component, C_{0it}^E and residual component, C_{0it}^R. All the covariances but the last are based on parameter estimates of the first-stage three-factor asset pricing model:

$$C_{0it}^D = (\beta_0^D + \gamma_0^D CR_1 + \eta_0^D CR_2)(\beta_i^D + \gamma_i^D CR_1 + \eta_i^D CR_2)V(f_{it}^D), \tag{3.12}$$
$$C_{0it}^G = (\beta_0^G + \gamma_0^G CR_1 + \eta_0^G CR_2)(\beta_i^G + \gamma_i^G CR_1 + \eta_i^G CR_2)V(f_t^G), \tag{3.13}$$
$$C_{0it}^{US} = (\beta_0^{US} + \gamma_0^{US} CR_1 + \eta_0^{US} CR_2)(\beta_i^{US} + \gamma_i^{US} CR_1 + \eta_i^{US} CR_2)V(f_t^{US}), \tag{3.14}$$
$$C_{0it}^E = \kappa_0\kappa_i\sqrt{V(ER_{0t-1})V(ER_{it-1})} + \psi_0\psi_i\sqrt{V(DY_{0t})V(DY_{it})}. \tag{3.15}$$

The inputs of the residual component derive from the second-stage DCCX estimation:

$$C_{0it}^R = \rho_{0it}^R\sqrt{V(u_{it})V(\epsilon_{it})}. \tag{3.16}$$

In analogy to the covariance, the variance of the US financial sector performance $V(ER_{0t})$ is given by:

$$
\begin{aligned}
V(ER_{0t}) = &(\beta_{0i}^{D} + \gamma_{0i}^{D} CR_1 + \eta_{0i}^{D} CR_2)^2 V(f_{it}^{D}) \\
&+ (\beta_{0}^{G} + \gamma_{0}^{G} CR_1 + \eta_{0}^{G} CR_2)^2 V(f_{t}^{G}) \\
&+ (\beta_{0}^{US} + \gamma_{0}^{US} CR_1 + \eta_{0}^{US} CR_2)^2 V(f_{t}^{US}) \\
&+ \kappa_0^2 V(ER_{0t-1}) + \psi_0^2 V(DY_{0t}) + V(u_{it}),
\end{aligned}
\tag{3.17}
$$

where β_{0i}^{D}, γ_{0i}^{D} and η_{0i}^{D} are parameters derived from the respective auxiliary regressions and u_{it} is the associated residual US excess return. In the same manner, the variance of the respective domestic financial sector performance $V(ER_{it})$:

$$
\begin{aligned}
V(ER_{it}) = &(\beta_{i}^{D} + \gamma_{i}^{D} CR_1 + \eta_{i}^{D} CR_2)^2 V(f_{it}^{D}) \\
&+ (\beta_{i}^{G} + \gamma_{i}^{G} CR_1 + \eta_{i}^{G} CR_2)^2 V(f_{t}^{G}) \\
&+ (\beta_{i}^{US} + \gamma_{i}^{US} CR_1 + \eta_{i}^{US} CR_2)^2 V(f_{t}^{US}) \\
&+ \kappa_i^2 V(ER_{it-1}) + \psi_i^2 V(DY_{it}) + V(\epsilon_{it}).
\end{aligned}
\tag{3.18}
$$

The underlying variance processes, $V(f_{it}^{US}), V(f_{it}^{G}), V(f_{it}^{D}), V(ER_{it-1}), V(DY_{it}), V(u_{it})$ and $V(\epsilon_{it})$, follow GARCH(1,1) processes. This dynamization constitutes a generalization of earlier asset pricing models, which account for crisis-related breaks in the covariance matrix at best (cf. Bekaert et al., 2014; Engle et al., 1992; Fama and French, 1993; Lintner, 1965; Ross, 1976, Sharpe, 1964).

3.4 Financial Integration and Financial Contagion

The following three-step analysis will demonstrate that episodes of turbulence have interfered with financial integration in recent years: US and global contagion drove the transmission of financial stress around the globe after the crash of Lehman Brothers during the Subprime Crisis. By contrast, in the Euro Crisis, financial stress increasingly concentrated in the original crisis countries due to US and domestic flight-to-quality. Hence, the Subprime Crisis was a global event and the Euro Crisis a regional event. Moreover, we spot inconsistencies between the correlation decomposition and the three-factor model, confirming that the fully dynamised Factor DCCX model delivers more reliable correlation estimates than asset pricing models abstracting from continuously time-dependent variances.

3.4.1 The Role of Common Shocks

In order to understand the common factors behind financial sector performance we estimate the three-factor asset pricing model initially in a panel context and afterwards running univariate regressions by country. The results indicate that the Subprime Crisis disseminated globally while the Euro Crisis concentrated on the euro area. Besides, the panel model discovers major underlying dynamics, but sometimes conceals substantial country-specific characteristics during the two crisis periods. This is a particular issue during the Subprime Crisis, when cross-country heterogeneity appeared to be a defining feature.

Table 3.1 shows the panel estimation results. With an adj. R-squared of 0.831, specification (1) already captures the majority of the existing variation. Modifications concerning cross-sectional fixed effects and cross-sectional weights do not improve the model fit. There is also no sign of residual serial correlation. Thus, the model seems well calibrated. However, since an eyeball test suggests heteroskedasticity in the residuals, we base the inference on heteroskedasticity-robust White standard errors (White, 1980). Moreover, Table C.3 in the appendix depicts country-specific univariate regressions. The model fit is again generally high as the adj. R-squared varies around 0.850. In four cases (AUT, GER, POR, UK), we detect residual serial correlation. Since the inclusion of further lags or moving averages does not improve the model's robustness, we leave this statistical artifact to be exploited in the second-stage DCCX estimation. We further employ Newey-West heteroskedasticity-robust standard errors (Newey and West, 1987), as the residuals display heteroskedasticity without exception.

The panel estimates in Table 3.1 indicate that the global factor exacerbated the already high international financial sector integration during the Subprime Crisis, whereas the various asymmetries in the US, global and domestic factors suggest regional transmission of the Euro Crisis. Under normal conditions, investor expectations introduce a mean-reverting element into financial sector performance through lagged excess returns. Beyond that, all three factors have a considerable positive impact on the performance of domestic financial sectors as the unconditional factor loadings are close to unity (0.974 to 1.261). The high relevance of non-domestic factors observed emphasises the international scope of the financial industry. During the Subprime Crisis, the global factor dependence increased, whereas the other two factor loadings remained unaltered.[65] In the Euro Crisis, the ties

[65] A comparison of our results with those of Bekaert et al. (2014) (loc. cit.: Table 8), who performed a closely related study on the wider stock market during the Subprime Crisis, indicates that a defining characteristic of shock transmission towards financial sectors in developed economies is their limited exposure to US and domestic shocks. Neither their emerging market peers nor non-financial corporations in developed countries show similarly strong exposure. Moreover, our panel estimates illustrate no crisis-related regime shift beyond changes in factor exposure. Since Bekaert et al. (2014) did not report such findings, the contagion from unidentified sources during the Subprime Crisis was apparently limited to financial sectors in emerging markets.

Table 3.1: Panel three-factor asset pricing model. The table shows panel estimates of the three-factor pricing model of Bekaert et al. (2014):

$$R_{it} = E_{t-1}[R_{it}] + \beta^{'} F_t + \gamma^{'} CR_1 F_t + \eta^{'} CR_2 F_t + \lambda CR_1 + \tau CR_2 + \epsilon_{it}.$$

t-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust according to White. Cross-section fixed effects are either included (Y) or excluded (N). Cross-section weights are either included (Y) or excluded (N). DW(1) denotes the Durbin-Watson statistic testing for one period-lagged serial correlation in the residuals. *** (**, *) indicates statistical significance at the 1% (5%, 10%) level.

	Domestic Financial Sector Performance			
Expectations	(1)	(2)	(3)	(4)
Div. Yield	-0.007	0.019	0.003	0.012
	(-0.91)	(1.55)	(0.25)	(0.36)
AR(1)	**-0.102*** **	**-0.106*** **	**-0.100*** **	**-0.104*** **
	(-8.26)	**(-8.46)**	**(-8.07)**	**(-7.86)**
Domestic factor				
Total	**0.974*** **	**0.977*** **	**0.907*** **	**0.910*** **
	(14.55)	**(14.49)**	**(7.23)**	**(7.23)**
Subprime crisis	-0.097	-0.101	-0.016	-0.020
	(-1.35)	(-1.39)	(-0.14)	(-0.18)
Euro crisis	**0.177** **	**0.174** **	**0.217** **	**0.213** **
	(2.16)	**(2.12)**	**(2.30)**	**(2.25)**
Global factor				
Total	**1.081*** **	**1.086*** **	**1.128*** **	**1.134*** **
	(15.10)	**(15.00)**	**(15.55)**	**(15.41)**
Subprime crisis	**0.172*** **	**0.166*** **	**0.186*** **	**0.179*** **
	(6.04)	**(5.72)**	**(3.72)**	**(3.56)**
Euro crisis	**0.202*** **	**0.196*** **	**0.253*** **	**0.247*** **
	(3.45)	**(3.34)**	**(3.24)**	**(3.15)**
US factor				
Total	**1.258*** **	**1.261*** **	**1.235*** **	**1.238*** **
	(18.21)	**(18.18)**	**(15.21)**	**(15.20)**
Subprime crisis	-0.031	-0.033	-0.006	-0.009
	(-0.81)	(-0.86)	(-0.15)	(-0.23)
Euro crisis	**-0.085*** **	**-0.088*** **	-0.054	-0.058
	(-2.18)	**(-2.24)**	(-1.22)	(-1.31)
Regime Shifts				
Subprime crisis	-0.033	-0.019	-0.101	-0.051
	(-0.63)	(-0.39)	(-1.56)	(-0.86)
Euro crisis	-0.023	0.034	**-0.061***	0.008
	(-0.79)	(1.28)	**(-1.65)**	(0.17)
Cross-section weights	Y	Y	N	N
Fixed effects	N	Y	N	Y
DW(1)	2.001	2.002	2.001	2.002
Adj. R-squared	0.831	0.831	0.782	0.782

of domestic financial sector performance to the domestic factor deepened but loosened vis-à-vis the US factor, while the global factor exposure remained elevated. Hence, the Subprime Crisis seems to have been primarily an international phenomenon, whereas the Euro Crisis was more of a regional one.

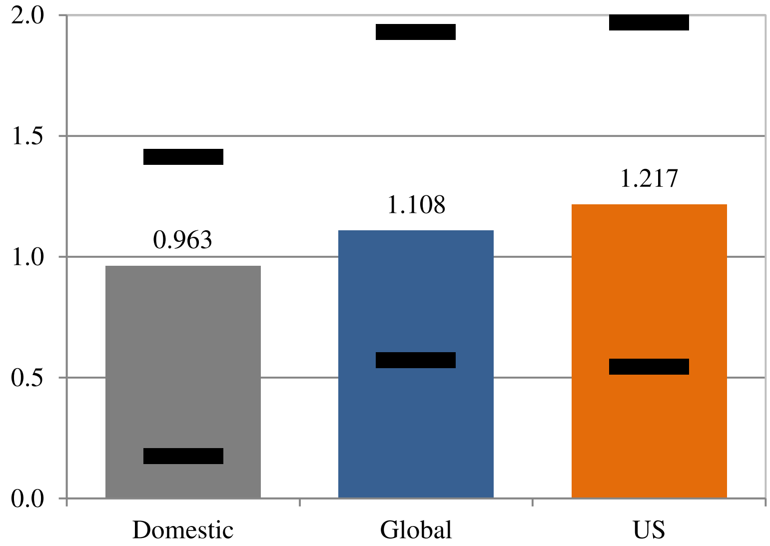

Figure 3.1: Coefficients of three-factor asset pricing model in normal times. This figure summarises the average coefficients of the domestic, global and US factor in normal times. Bars denote the observed minimum and maximum factor loadings. The evidence is based on univariate estimates of the three-factor capital asset pricing model. Detailed regression results are presented in Table C.3 in the appendix.

Turning to the country-specific univariate regressions, the results widely reconfirm our previous findings, but also reveal widespread heterogeneity across countries in episodes of stress. For instance, the unconditional coefficients, β_i', in Figure 3.1 lie in the same range as before (0.963 to 1.217) and investor expectations pre-dominantly cause the mean-reversion. Nevertheless, the significance of certain parameters in the panel model is often backed by rather few countries. This applies particularly to the crisis-related asymmetries shown in Figure 3.2: during the Subprime Crisis, merely seven countries support a significant rise in the global factor, whereas two (three) featured an increase in the domestic factor (US factor) and four (three) a decrease. However, only the global factor survives in the panel model. A less confused picture arises for the Euro Crisis: six countries show a significant rise in the global factor, eight (one) countries experienced an increase in the domestic factor (US factor) and four (six) a drop. This time, the panel model upholds tighter dependence on the global and domestic factors and looser dependence on the US factor. This leads us to conclude that cross-sectional heterogeneity disguises some opposing country-specific characteristics, which the univariate regressions eventually uncover. The disturbance was most pronounced during the Subprime Crisis.

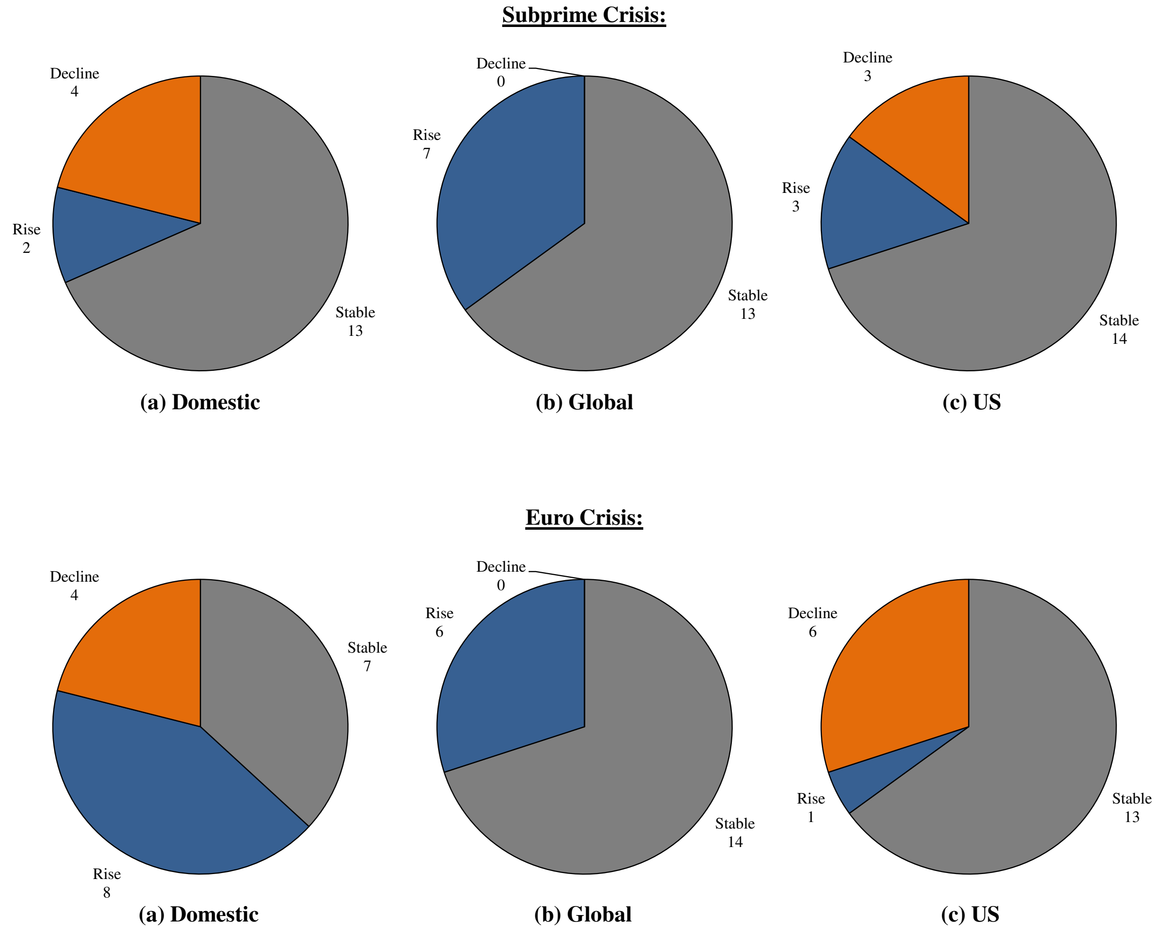

Figure 3.2: Crisis-related shifts in country-specific three-factor asset pricing model. This figure summarises the frequency and direction of crisis-related shifts in the (a) domestic, (b) global, (c) US factor of the three-factor asset pricing model in the Subprime Crisis and Euro Crisis. The evidence is based on univariate estimates of the three-factor capital asset pricing model. Detailed regression results are presented in Table C.3 in the appendix.

Despite the observed heterogeneity, we detect some geographical patterns. In the Subprime Crisis, six of the domestic financial sectors witnessing a rise in global factor dependence were located outside the euro area, three of which are Asian countries. By contrast, during the Euro Crisis, four (six) of the six (eight) surges in the global factor (domestic factor) and four of the six drops in the US factor involved financial sectors in the euro area. Thus, there was an observable geographical shift in the vulnerability of financial sectors towards the euro area over time.

The auxiliary regressions (cf. Figure C.1 in the appendix) reconfirm this impression.[66] The US residuals negatively relate without exception to the other countries' domestic factors in normal times. During the Subprime Crisis, a systematic decline occurred in the domestic factor exposure in all but one country. In the Euro Crisis, one decrease in domestic factors was accompanied by three surges. All of these affected countries in

[66] The residuals obtained from the auxiliary regressions do not display serial correlation, but strong heteroskedasticity.

the spotlight of the Euro Crisis (GRE, ITA, SPA) and widely offset the usually negative dependence. This hints at a decoupling of thedomestic financial sectors at the centre of upheaval from US excess performance.

In our view, the observed fluctuations in factor dependencies during periods of stress are likely to be due to evaporating common funding sources in the Subprime Crisis and sovereign risk exposure in the Euro Crisis. The reliance on common funding sources explains well why we find an unopposed rise in global factor dependence, while the evidence for the other two factors is vaguely consistent: as financial institutions were strongly intertwined on a global scale preceding the Subprime Crisis, in particular via short-term funding (cf. Brunnermeier, 2009, Gorton and Metrick, 2012, Longstaff, 2010), the gradual drying up of common funding sources culminating after the demise of Lehman Brothers in September 2008 made financial institutions vulnerable to common shocks. The regional focus of the Euro Crisis, notably the rise in domestic factors paired with the decoupling from the US factor, favours sovereign risk as the underlying driver (Lane, 2012). The simultaneous and widespread increase of the global factor in the euro area further indicates that global initiatives on regulatory reform, such as Basle III, agreed on by the G20 countries in 2010 to 2011, may have added to the sovereign risk. After all, both explanations are consistent with the observed heterogeneous vulnerability in the former crisis period, which later shifts towards the euro area. Hence, crisis-related shifts in factor dependence hint at common funding sources and mounting sovereign risk as the primary sources of changes in the shock transmission across countries.

3.4.2 The Role of Extreme Events and Repo Market Failure

Now, we examine how extreme events and disorder in the repo market feed back into the residual performance co-movement of domestic financial sectors around the globe. Given that the first-stage residuals consistently show volatility clustering, we use the distinct ability of DCC-type models to deliver undistorted correlation estimates under heteroskedasticity. To this end, we follow the two-stage estimation procedure in subsection 3.3.2.

When screening residual excess returns, the DCCX model sometimes reveals substantial residual co-movement. The first-stage GARCH(1,1) variance estimates are presented in Table C.5 in the appendix. The residuals from the country-specific three-factor asset pricing model and the auxiliary regressions display strong heteroskedasticity and a high level of persistency in all but one case, as the parameters δ and θ are both significant and close to unity. The results of the second-stage DCC and DCCX estimations are exhibited in Figure 3.3. The DCC model suggests the widespread existence of systematic residual co-movement as ten out of nineteen countries show hidden constant correlation. In another four cases, the α coefficient is significant. The richer DCCX model taking extreme domestic and US events as well as repo market failure into account deciphers other concealed residual correlation dynamics: eleven domestic financial sectors respond to lagged unexpected repo failures, six depend on previous extreme domestic news and another three depend on extreme US shocks. In addition, the number of significant α coefficients doubles from four to eight. Besides, the correlation differential between the DCCX- and the DCC-implied residual correlation (cf. Figure C.2 in the appendix) illustrate that the residual correlations considering asymmetries and repo failures allows vary substantially more, especially during periods of financial stress. The evidence collected demonstrates that the DCCX model discovers substantial hidden residual correlation during periods of financial stress.

Surprisingly, the newly discovered residual correlation dynamics mostly indicate declining future co-movement. Thus, spillovers from extreme news shocks and repo market failure primarily produce flight-to-quality rather than contagion according to our previous notion. More precisely, extreme domestic and US news shocks consistently provoke lower residual correlations as their respective parameters ϕ_1 and ϕ_2 are negative. The coefficient ϕ_3 is also mostly negative (eight of eleven). This finding is further corroborated by the fact that the average residual correlation is lower when markets are stressed (cf. Figure C.3). However, they experience episodes of formidable amplitude during crisis periods (cf. Figure C.2 in the appendix) although residual correlations are typically small. Thus, ignoring residual co-movement would produce erroneously exaggerated correlations vis-à-vis the US financial sector. This is an astonishing finding since the diagnostic tests carried out in subsection 3.4.1 predominantly indicated the absence of such residual serial correlation.

Portfolio rebalancing activities and policy interventions both offer plausible explanations for the observed flight-to-quality subsequent to extreme events and repo market failure. In the case of portfolio rebalancing, the examined disturbances may interfere with portfolio allocations, creating a need for investors involved in the financial sector to adjust their portfolios. Provided that investors hold marginally distinct portfolios after the shock, heterogeneous rebalancing activities eventually lead to decoupling correlations. Another potential reason is government and central bank interventions. Governments and central banks have an incentive to bail out ailing financial institutions at the height of a financial crisis to avoid losses for voters and spillovers to other financial markets and the real economy. Extreme events and repo market failures might therefore act as indicators of imminent bailouts. In fact, over the course of both crises, policy makers massively intervened following peaks in turmoil: after the Lehman Crash in September 2008, governments around the globe equipped struggling financial institutions with equity and state guarantees, while central banks kept them afloat with unlimited Bagehot-style (1873) liquidity injections (cf. Claessens et al., 2011; Laeven and Valencia, 2010). Later, when

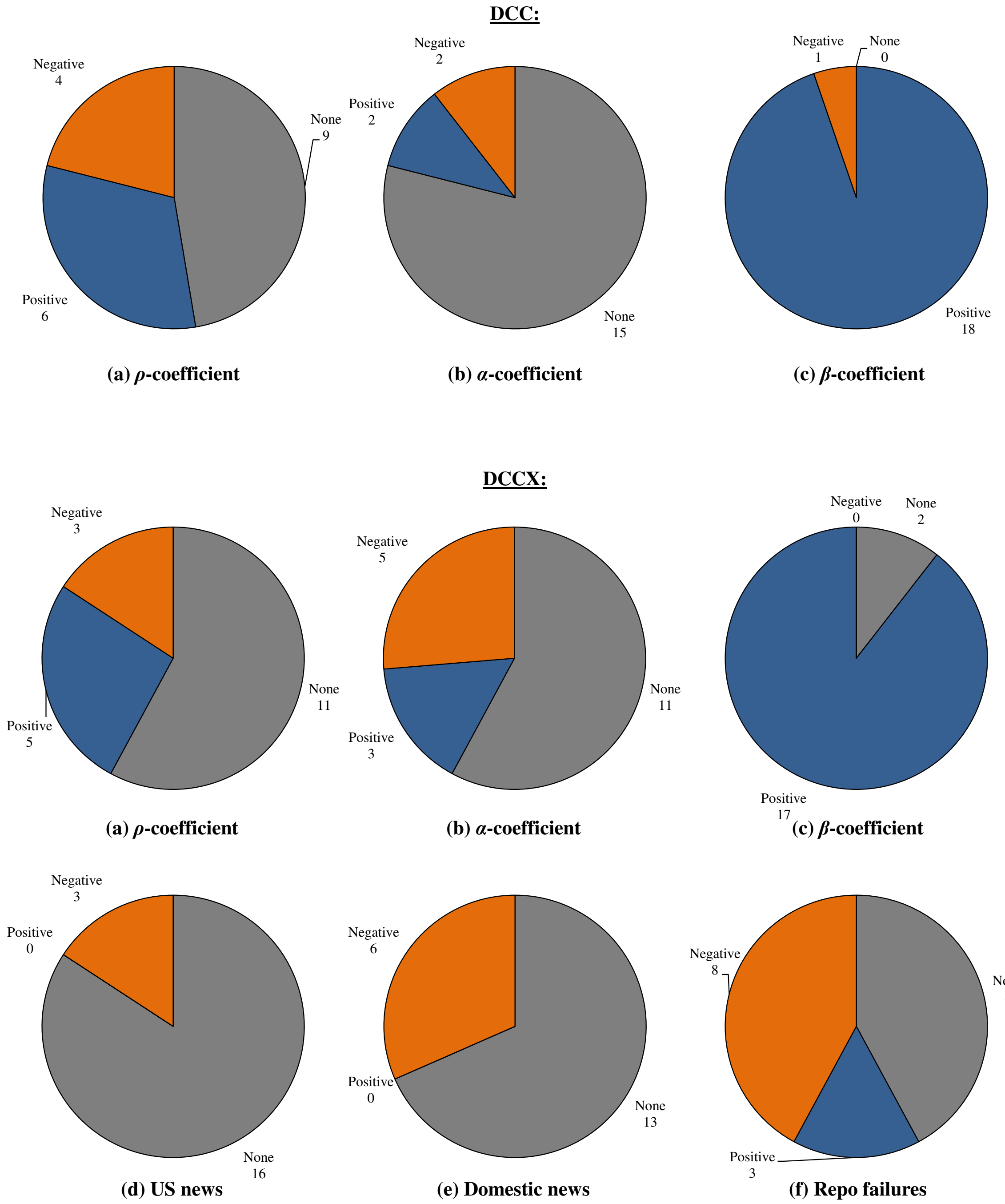

Figure 3.3: DCC- and DCCX-implied correlation dynamics. This figure summarises the frequency and direction of the correlation dynamics resulting from the DCC and DCCX models. The evidence is based on estimates of the DCC and DCCX model. Detailed regression results are presented in Table C.6 in the appendix.

Greece, Ireland and Portugal were incapable of rolling over their sovereign debt, orchestrated bailouts protected bond investors from losses and the European Central Bank's Outright Monetary Transactions Program secured the liquidity position of financial institutions (Cour-Thimann and Winkler, 2013). As a result, the tensions in the financial markets receded (cf. Cour-Thimann and Winkler, 2013; Claessens et al., 2011; Laeven and Valencia, 2010).

In summary, the proposed DCCX correlation structure reveals otherwise hidden flight-to-quality following extreme news shocks and mounting repo failures. Two plausible rationales for this behaviour are portfolio rebalancing and policy interventions, such as government bailouts or central bank interventions. As a result, financial sectors decouple vis-à-vis their US equivalent following peaks in financial turmoil, thereby diminishing the global systemic risks.

3.4.3 The Role of Contagion and Flight-to-Quality in Financial Integration

The final step of our analysis is to accurately characterise the financial sector co-movement over time. Therefore, we inspect the aggregate correlation and its components visually and by running regressions. We uncover that US and global contagion became pivotal in infecting financial institutions around the world after Lehman Brothers crashed in the Subprime Crisis, whereas progressively accelerating US and domestic flight-to-quality best characterise the Euro Crisis. Moreover, we spot prominent inconsistencies between the correlation decomposition and the three-factor asset pricing model.

Although the correlations and thus financial integration vis-à-vis the US financial sector seem generally stable, some exceptional patterns materialised during the two crises (cf. ??): with the early signs of turmoil arriving in August 2007, the correlations initially ramped up, before rapidly easing again. Having reached their crisis lows in mid-2008 (0.5x mean correlation), the financial sector co-movement swiftly gained momentum over the summer—especially after the demise of Lehman Brothers in September—eventually hitting their crisis peaks in October 2008 (1.5x mean correlation). Later, during the Euro Crisis, the four countries at the centre of investor concerns—GRE, ITA, POR, SPA—also showed the most prominent behaviour: while correlations by and large tended to stabilise at pre-crisis levels, these countries strongly decoupled vis-à-vis the US financial sector, in particular subsequent to the last IMF-led bailout in May 2011.[67] This tendency was only briefly interrupted by two episodes of surging correlations: the smaller one occurred in mid-2010, following the Greek bailout, and the larger one in mid-2011 (1.5x mean correlation), when investors became increasingly concerned about the Italian and Spanish sovereign risk (Lane, 2012).

Investigating the sources of financial integration, a visual inspection of Figures 3.5 and 3.6 reveals that the US and global components were both positive, while the domestic one was consistently negative. The US component alone accounted for roughly two-thirds of the overall correlation, followed in size by the global and domestic ones.[68] As for the aggregate

[67] The IMF-led bailout of Cyprus in March 2013 lies outside our sample period.

[68] This finding is partly due to the construction of the global factor and domestic factors. Since the orthogonalization procedure essentially removes some variation from the global and domestic factors,

correlation, the three components were remarkably stable prior to financial stress. During both crises, the US component dominated the aggregate correlation dynamics, such as the ramp-up in September 2008 and the gradual decoupling of GRE, ITA, POR and SPA since late 2009. By contrast, the domestic component alleviated some of the increased co-movement in the Subprime Crisis, but reinforced the decoupling of the four crisis countries in the Euro Crisis. Furthermore, the DCCX-implied residual correlations shown in Figure 3.6 (the expectations component is negligibly small and therefore omitted) were typically small (a mean of 0.02 percentage points), but drastically fluctuated during crisis episodes, reducing (increasing) the overall correlations by up to -21.9 (17.6) percentage points. Hence, the impact of the different components on financial integration, particularly during episodes of stress, remains to some extent inconclusive.

In order to clear up these ambiguities, we perform the following complementary country-specific ($i \neq 0$) univariate regressions in the tradition of Chiang et al. (2007) to explore the regime shifts in financial sector dependence over and above expectations in the wake of financial turmoil. The first contains one regime dummy for each crisis (CR_1 and CR_2):

$$\rho_{0it} = \upsilon_{i0} + \upsilon_{i1}\rho_{0it-1} + \upsilon_{i2}CR_1 + \upsilon_{i3}CR_2 + z_{it}. \tag{3.19}$$

The second one breaks each crisis down further into a pre- and post-Lehman Brothers period (Subprime Crisis: CR_1^{Pre} and CR_1^{Post}) and a pre- and post-IMF bailout period (Euro Crisis: CR_2^{Pre} and CR_2^{Post}):

$$\rho_{0it} = \upsilon_{i0} + \upsilon_{i1}\rho_{0it-1} + \upsilon_{i2}CR_1^{Pre} + \upsilon_{i3}CR_1^{Post} + \upsilon_{i4}CR_2^{Pre} + \upsilon_{i5}CR_2^{Post} + z_{it}. \tag{3.20}$$

υ_{i0} measures the unconditional correlation and υ_{i1} controls for first-order serial correlation.[69] The parameters υ_{i2}, υ_{i3}, υ_{i4} and υ_{i5} identify regime shifts during the Subprime Crisis and the Euro Crisis. z_{it} is the error term.

Our results in Figure 3.7 portray how vigorously contagion hit numerous financial sectors around the globe following the demise of Lehman Brothers in September 2008:[70] Thirteen domestic financial sectors display positive regime shifts with an average magnitude of about 16.3% in terms of the unconditional correlation. However, in the period leading up to the bank's collapse, we find zero contagion and instead five cases of flight-to-quality averaging - 12.8%. When considering the Subprime Crisis in its entirety, contagion survives in merely six cases and flight-to-quality in another one. Thus, despite being fierce, both contagion and flight-to-quality were obviously rather short-lived. Regarding the sources of contagion, the US component and the global component already account for all

their variances are lower, too, thereby losing weight in the calculation of correlations.

[69] One reason for including a first-order autoregressive term in the equation is to exploit serial correlation in the expectations and residual correlation component. Second, since all the variances follow a GARCH(1,1) process, the aggregate correlations might show the same pattern.

[70] The detailed regression results are presented in the appendix.

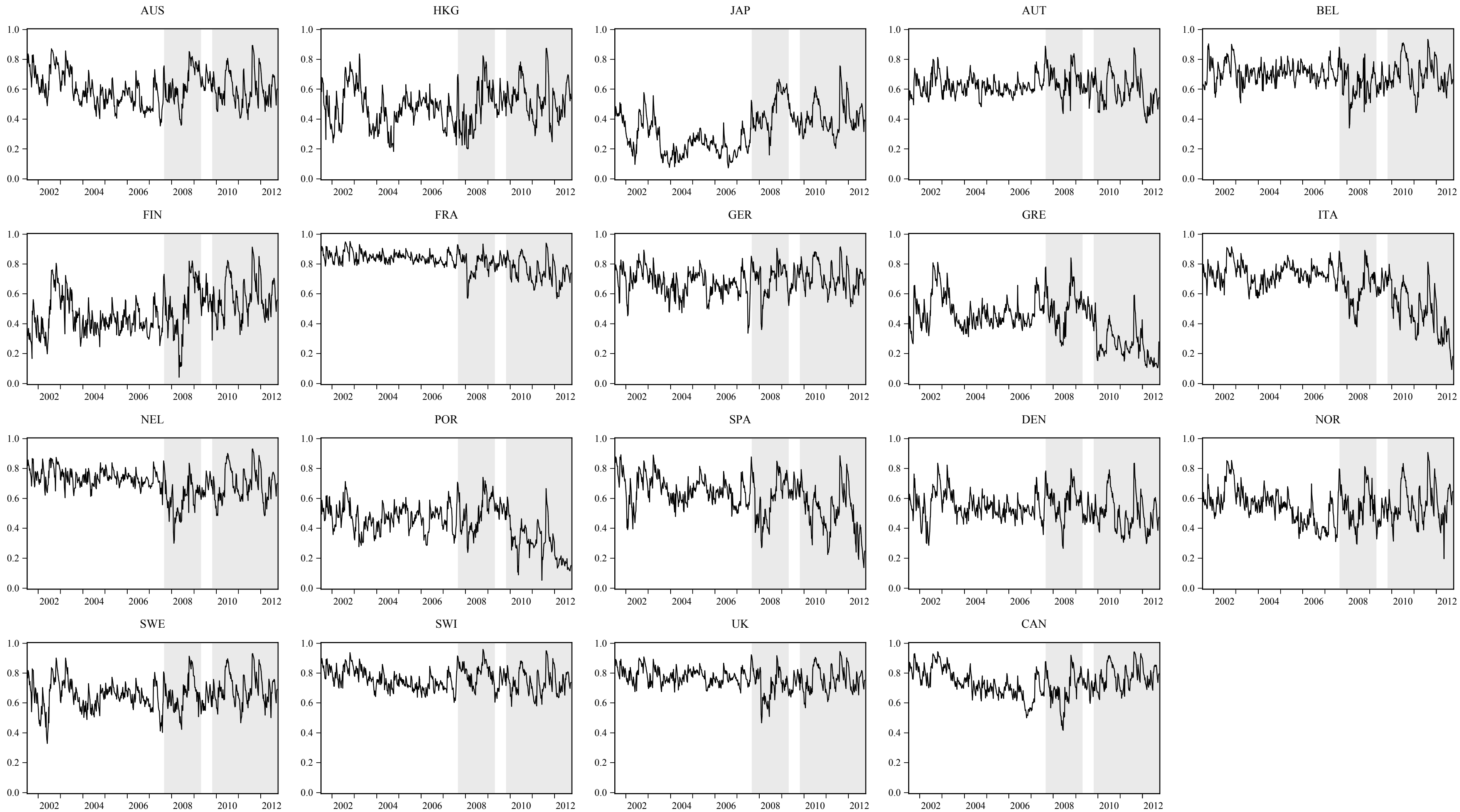

Figure 3.4: Aggregate correlations. This figure shows the weekly overall correlations of the US financial sector vis-a-vis its respective domestic equivalents between July 4, 2001 and September 26, 2012. The left (right) grey-shaded area denotes the Subprime Crisis (Euro Crisis).

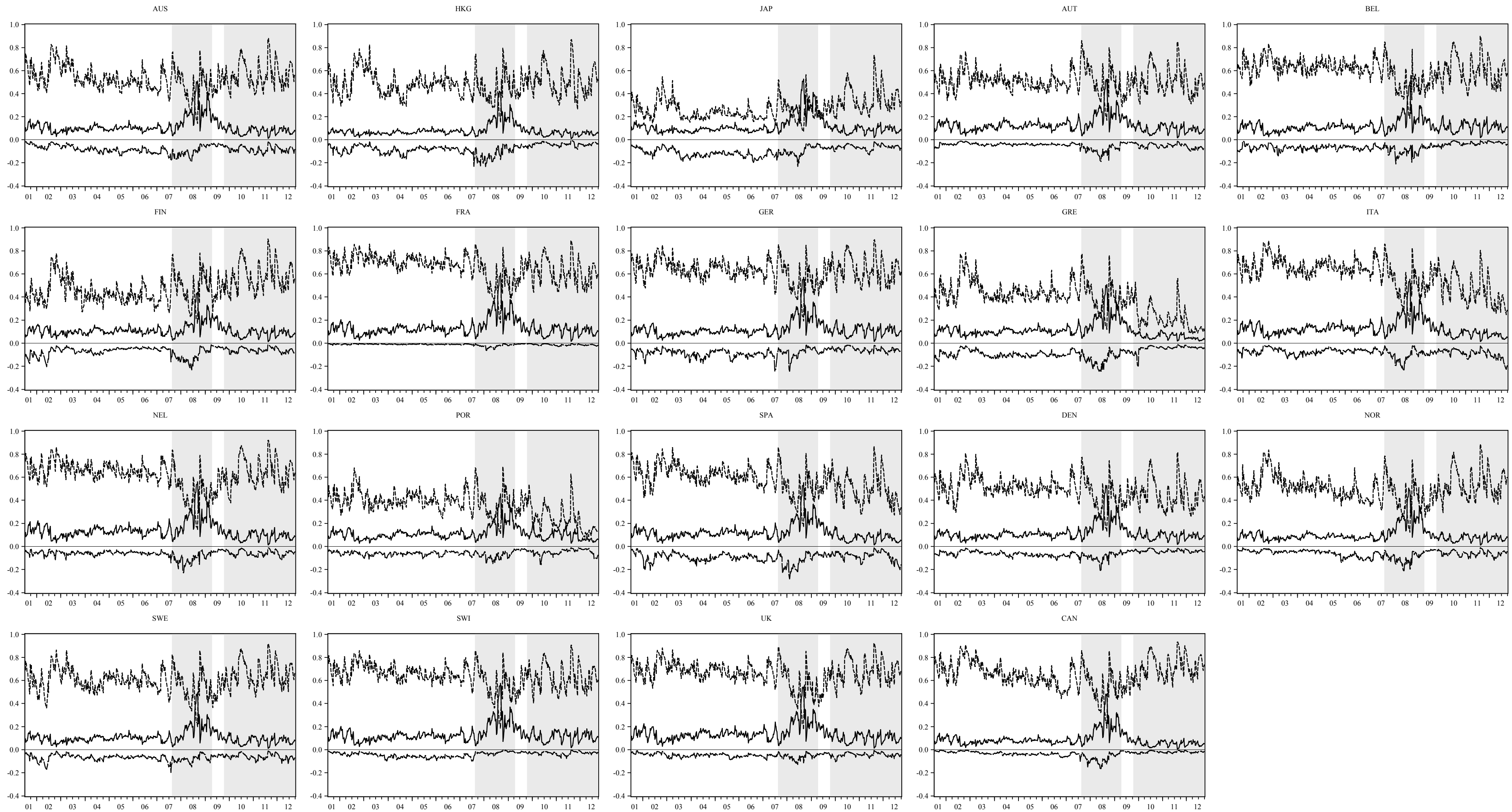

Figure 3.5: US, global and domestic correlation components. This figure shows the weekly correlations of the US financial sector vis-a-vis its respective domestic equivalents attributable to the US, global and domestic components between July 4, 2001 and September 26, 2012. The upper dashed line denotes the US factor, the solid line the global financial factor and the lower dashed line the domestic factor. The left (right) grey-shaded area denotes the Subprime Crisis (Euro Crisis).

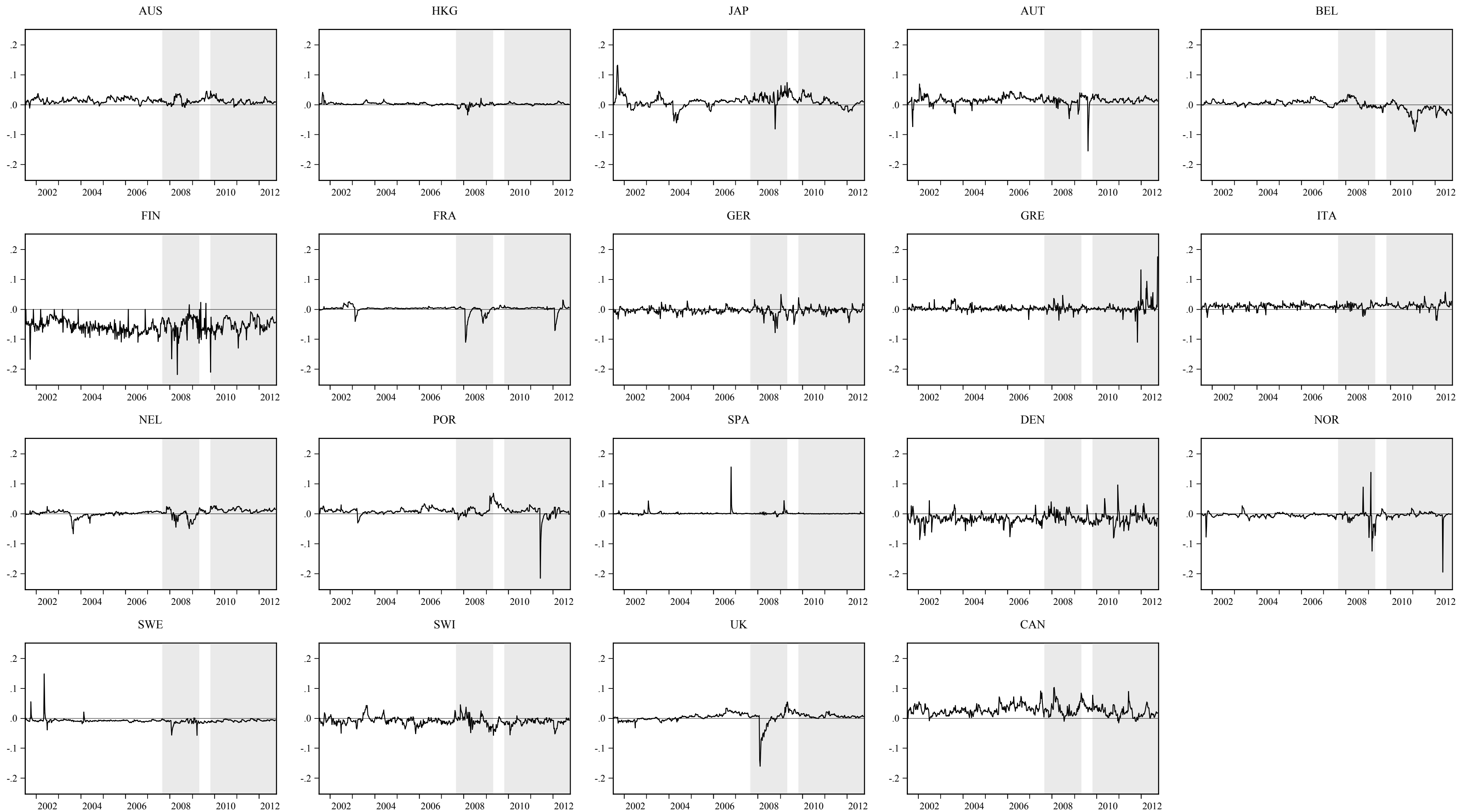

Figure 3.6: Residual correlation component. This figure shows the weekly correlations of the US financial sector vis-a-vis its respective domestic equivalents attributable to the residual component between July 4, 2001 and September 26, 2012. The left (right) grey-shaded area denotes the Subprime Crisis (Euro Crisis).

the cases of contagion and flight-to-quality in the overall correlations. The domestic and residual correlation components are nevertheless relevant, since they not only eliminated some cases of contagion (13 vs. 16), but also mitigated the size of contagion over the entire crisis period (7.5% vs. 13.3%). Hence, the contagion was widespread and particularly intense following the crash of Lehman Brothers.

On the other hand, the Euro Crisis was marked by considerable flight-to-quality and clearly concentrated in Europe, particularly in the euro area, as Figure 3.8 further highlights. Prior to and after the IMF-led bailouts, five Euro member states consistently displayed sizeable flight-to-quality (around -20.1%) and another member state contagion. At the centre of investor concerns were four of the former countries—GRE, ITA, POR, SPA—, while the sole contagion country (FIN) was an AAA-rated euro member. Thus, investors tended to relocate their funds towards "safe havens" within the currency area. Besides, since the intensity of flight-to-quality (- 19.3% to - 28.8%) and contagion (16.6% to 24.0%) accelerated over the course of the Euro Crisis, so did the observed excessive disintegration of financial sectors. Regarding the drivers, the US component emerges as the single most important source, not only accounting for all the detected cases of flight-to-quality and contagion, but also closely resembling their sizes. The domestic components further appear to have reinforced flight-to-quality in the post-IMF-bailout period. The Euro Crisis was accordingly a regional event characterised by gradually increasing disintegration of European financial sectors—most notably those of the four crisis countries—from the US and thus the largest financial system in the world.

When contrasting the investigated sources of overall correlation dynamics with those of the three-factor asset pricing model we observe widespread inconsistencies. First, the three-factor panel model predicts rising co-movement during the Euro Crisis driven by the global factor, but the global correlation component displays no analogous increase. Second, the country-specific regressions indicate far more global contagion during the Subprime Crisis (7 vs. 3) and the Euro Crisis (8 vs. 0) than the correlation decomposition.[71] Turbulent periods therefore tend to dominate even variance processes incorporating crisis-related jumps as they do not adequately account for volatility peaks. Hence, even a sophisticated three-factor asset pricing model would appear to mischaracterise financial sector co-movement, were it to ignore the continuous time-varying variances. Since in the present case all the factors and most residuals experience considerable volatility clustering, the proposed Factor DCCX model provides substantial improvements in examining financial sector integration.

In a nutshell, the correlation decomposition uncovered that after Lehman Brothers crashed during the Subprime Crisis, US and global contagion became pivotal in infecting financial institutions around the world, whereas the Euro Crisis was characterised by progressively

[71] It is impossible to benchmark the domestic correlation component against the domestic correlation implied by the three-factor model as the former depends on auxiliary regressions of the US residual.

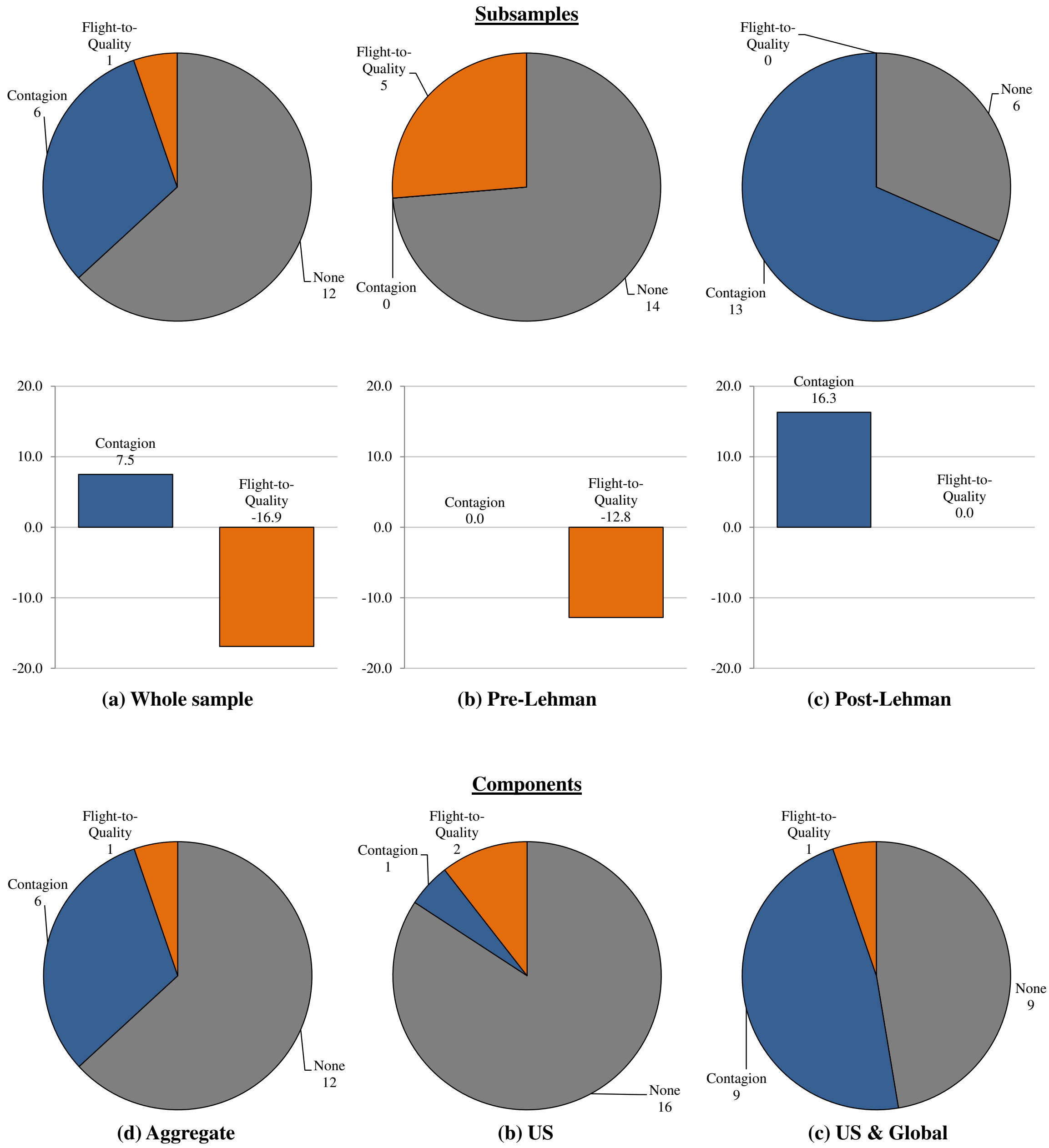

Figure 3.7: Contagion and flight-to-quality in the Subprime Crisis. This figure summarises the frequency (pie charts) and size (bar charts, in %) of contagion and flight-to-quality in the Subprime Crisis. The analysis is split into subsamples (pre- and post-Lehman) and components (US, US and global). The evidence is based on country-specific regressions of aggregate financial sector co-movement on a set of control and regime variables. More details are given in Panel A of Table C.7 and Table C.8 in the appendix.

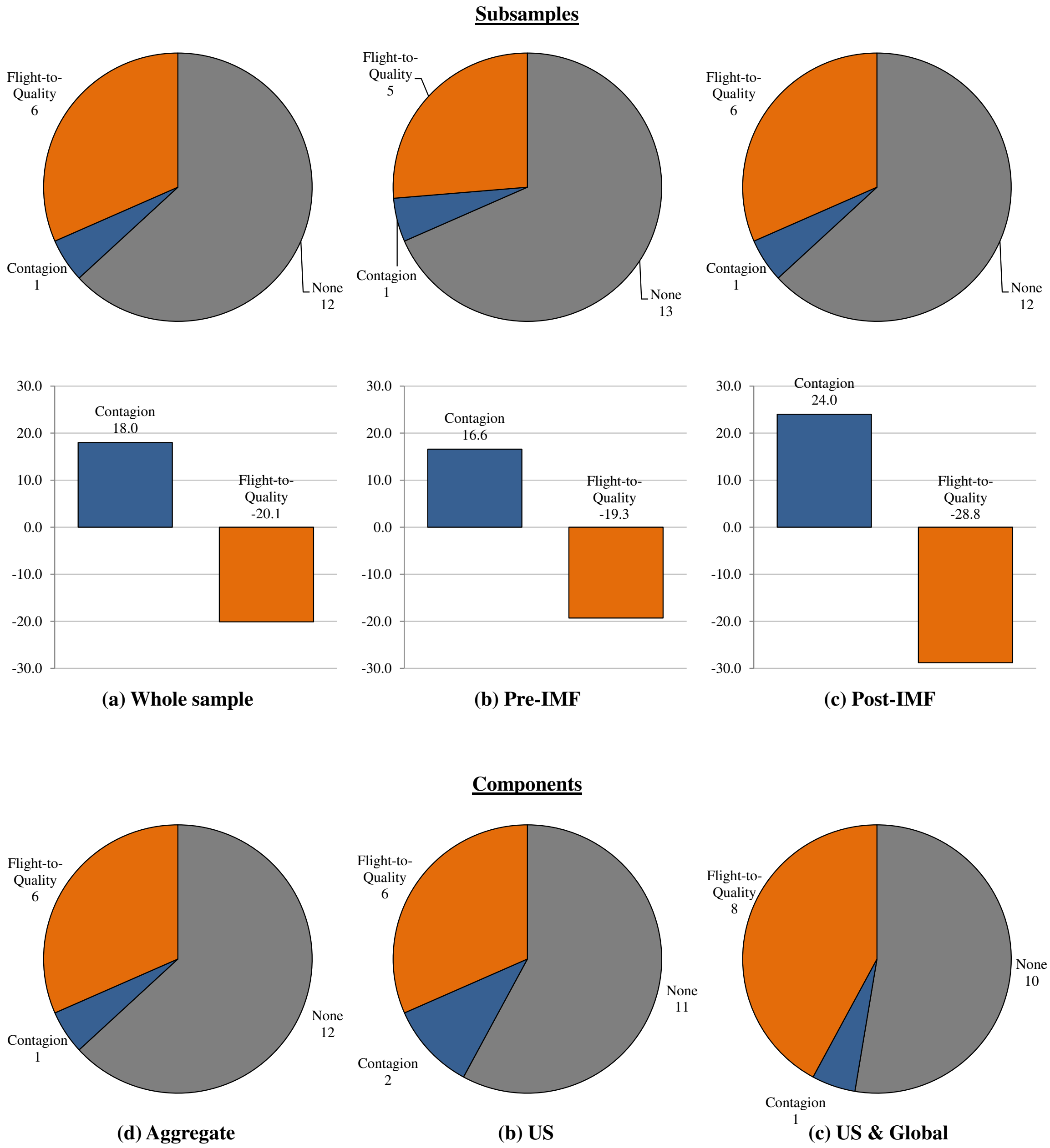

Figure 3.8: Contagion and flight-to-quality in the Euro Crisis. This figure summarises the frequency (pie charts) and size (bar charts, in %) of contagion and flight-to-quality in the Euro Crisis. The analysis is split into subsamples (pre- and post-IMF) and components (US, US and global). The evidence is based on country-specific regressions of aggregate financial sector co-movement on a set of control and regime variables. More details are given in Panel B of Table C.7 and Table C.8 in the appendix.

accelerating US and domestic flight-to-quality. Hence, the US financial sector constituted an important channel for spreading financial stress in the former crisis, but helped to contain turmoil regionally in the latter. Judging by their respective transmissions the Subprime Crisis can be considered a global event and the Euro Crisis a more regional one. Moreover, we identified prominent inconsistencies between the correlation decomposition and the three-factor model. These findings demonstrate the superior ability of the Factor DCCX model to disentangle the dynamics underlying financial contagion and flight-to-quality over the course of crisis periods.

3.5 Conclusions

The US financial sector is today unparalleled in terms of size and liquidity in the world. For this reason, it represents a natural benchmark for assessing the degree of integration of any other country into the world financial system. We studied how well 19 countries are integrated with the US financial sector and the effect that the Subprime Crisis (2007-09) and the Euro Crisis (2009 until recently) had on these ties.

It emerged that financial integration, measured by the co-movement of domestic financial sector performance vis-à-vis its US equivalent, is globally high. However, excessive co-movement deviating from fundamentals interfered with financial integration during the Subprime Crisis and the Euro Crisis. In the former crisis, US and global contagion spread financial turmoil around the world after the collapse of the investment bank Lehman Brothers, whereas US-driven flight-to-quality initiated progressive decoupling of European crisis countries (Greece, Italy, Portugal, Spain) from their US equivalent during the latter crisis. Nevertheless, domestic and residual shocks added a flight-to-quality element to financial sector co-movement in both turmoil periods. They thereby remarkably lowered the magnitude of contagion in the Subprime Crisis (from 13.3% to 7.5%) and reinforced the flight-to-quality in the Euro Crisis (from -15.2% to -20.1%). Although the domestic component is usually more influential, residual co-movement becomes sizeable in the wake of stress when unexpected repo failures as well as extreme news shocks spill over negatively into residual correlations. Hence, contagion and flight-to-quality impaired financial integration during both crises, while their size considerably depended on the various components.

Our findings provide important insights from a systemic risk perspective. The rescue measures implemented supposedly contributed to isolating both crises, as central banks and governments strongly intervened in financial markets following peaks in turmoil. In this regard, the interventions of US policy makers promised greater potential to contain financial stress from spreading than those of domestic policy makers. However, the exact implications of rescue measures depended on the nature of shock transmission in the respective crisis. Faced with contagion, the mitigating effect of domestic and residual shocks is desirable to bring co-movement back to its fundamentals, for instance after the Lehman collapse. On the other hand, the same effect might create unintended new challenges in the light of flight-to-quality, similar to the Euro Crisis. In fact, flight-to-quality may encourage excessive risk-taking on the side of financial institutions domiciled outside the euro area due to swift capital inflows. By contrast, the European Central Bank should be worried about flight-to-quality from certain member states, as it impedes the homogeneity of financial sectors—a pre-requisite for maintaining an effective monetary policy in a currency union (Mundell, 1961). Bearing this in mind, it is particularly alarming that flight-to-quality as a mirror of excessive capital withdrawals from the crisis countries even accelerates over time. From a national regulator's point of view, flight-to-quality also increases the probability of inter-sectoral propagation within crisis countries, since receding financial integration results in a growing lack of accessible capital for corporations, too. Hence, the consequences of policy actions taken to contain the dissemination of financial stress have the potential to create new challenges with respect to systemic risk.

Finally, the proposed Factor DCCX model forms an effective tool for risk management purposes because it is tailored to filter out correlation patterns that are otherwise hidden by volatile market conditions. In the present case, we decipher flight-to-quality concealed in the residual excess returns following extreme domestic and US news shocks as well as unexpected repo market failures. Given the extent of inconsistencies observed between the correlation decomposition and the three-factor asset pricing model, taking more complex correlation structures and continuous heteroskedasticity into account actually pays off. Hence, when quantifying a portfolio's or financial institution's vulnerability towards macro-financial risk scenarios, the Factor DCCX model yields superior correlation estimates in comparison with less elaborate asset pricing models.

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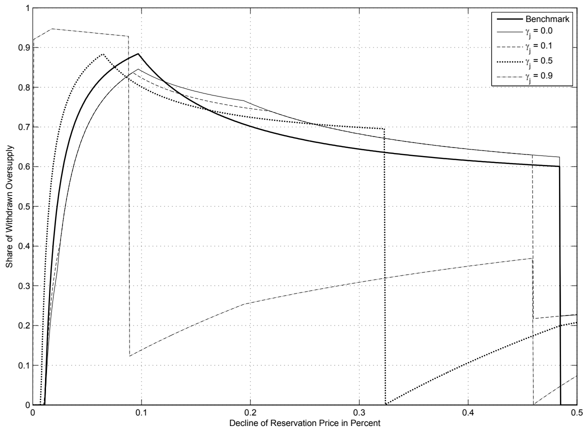
Appendix A

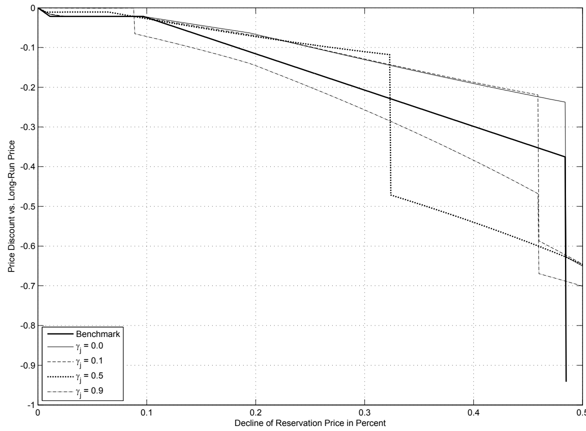
Housing Market Downturns

Table A.1: Model Parameterization. This table contains the parameters and variables by model. MP (UP, FS, PS) denotes "monetary policy" ("urban policy", "financial stimuli", "policy scenarios").

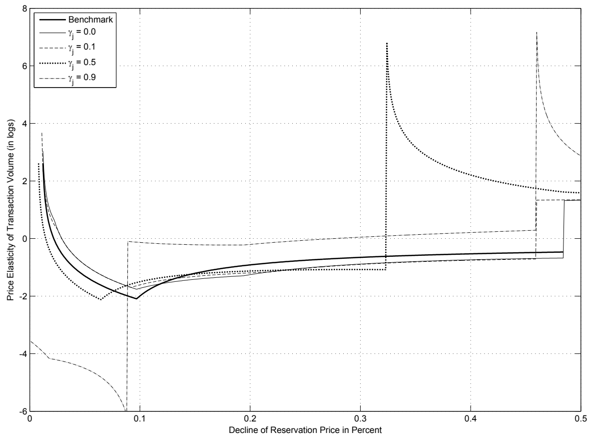
Model	Variables					Reserv. Price		Supply Elast.		Cross-Segm. Comp.		Banking Sector				Shock Co-Move.
Homogeneous	r	δ	T	ltv_1	ltv_2	α_{10}	α_{20}	β_1	β_2	γ_1	γ_2	l_1	l_2	ϕ_1	ϕ_2	ρ
Standard	0.05	0.02	10	—	—	2	—	1	—	—	—	1	—	0.03	—	—
Heterogeneous																
Standard	0.05	0.02	10	—	—	2	2	1	1	0.5	0.5	1	1	0.03	0.03	0.5
Cross-Segment Competition																
#1	0.05	0.02	10	—	—	2	2	1	1	0.0	0.0	1	1	0.03	0.03	0.5
#2	0.05	0.02	10	—	—	2	2	1	1	0.1	0.1	1	1	0.03	0.03	0.5
#3	0.05	0.02	10	—	—	2	2	1	1	0.5	0.5	1	1	0.03	0.03	0.5
#4	0.05	0.02	10	—	—	2	2	1	1	0.9	0.9	1	1	0.03	0.03	0.5
Co-Movement																
#1	0.05	0.02	10	—	—	2	2	1	1	0.5	0.5	1	1	0.03	0.03	0.0
#2	0.05	0.02	10	—	—	2	2	1	1	0.5	0.5	1	1	0.03	0.03	0.1
#3	0.05	0.02	10	—	—	2	2	1	1	0.5	0.5	1	1	0.03	0.03	0.5
#4	0.05	0.02	10	—	—	2	2	1	1	0.5	0.5	1	1	0.03	0.03	0.9
Policy variables																
MP: #1	0.01	0.02	10	—	—	2	2	1	1	0.5	0.5	1	1	0.03	0.03	0.5
MP: #2	0.05	0.02	10	—	—	2	2	1	1	0.5	0.5	1	1	0.03	0.03	0.5
MP: #3	0.09	0.02	10	—	—	2	2	1	1	0.5	0.5	1	1	0.03	0.03	0.5
UP: #1	0.05	0.01	10	—	—	2	2	1	1	0.5	0.5	1	1	0.03	0.03	0.5
UP: #2	0.05	0.02	10	—	—	2	2	1	1	0.5	0.5	1	1	0.03	0.03	0.5
UP: #3	0.05	0.03	10	—	—	2	2	1	1	0.5	0.5	1	1	0.03	0.03	0.5
FS: #1	0.05	0.02	5	—	—	2	2	1	1	0.5	0.5	1	1	0.03	0.03	0.5
FS: #2	0.05	0.02	10	—	—	2	2	1	1	0.5	0.5	1	1	0.03	0.03	0.5
FS: #3	0.05	0.02	15	—	—	2	2	1	1	0.5	0.5	1	1	0.03	0.03	0.5
PS: #1	0.01	0.03	15	—	—	2	2	1	1	0.5	0.5	1	1	0.03	0.03	0.5
PS: #2	0.05	0.02	10	—	—	2	2	1	1	0.5	0.5	1	1	0.03	0.03	0.5
PS: #3	0.09	0.01	5	—	—	2	2	1	1	0.5	0.5	1	1	0.03	0.03	0.5
US Housing Market Crash																
Standard	0.05	0.02	10	0.9	0.8	2	3.45	1	1	0.5	0.5	1	2	0.06	0.06	0.5



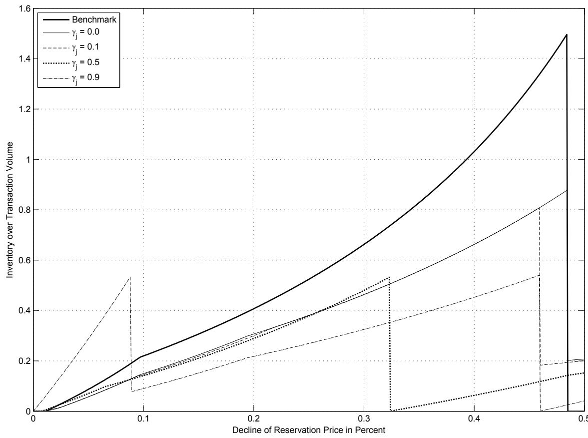
(a) Share of withdrawn oversupply.



(b) Price discount vs. long-run house price.

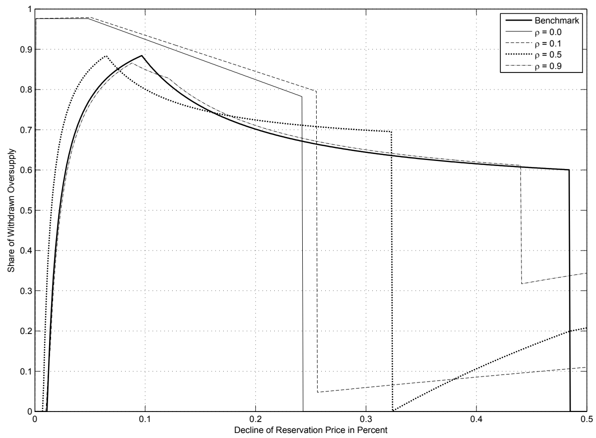


(c) Price elasticity of home sales.

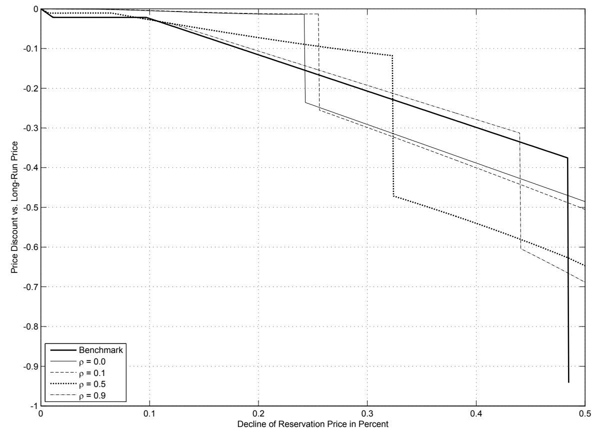


(d) Inventory over home sales.

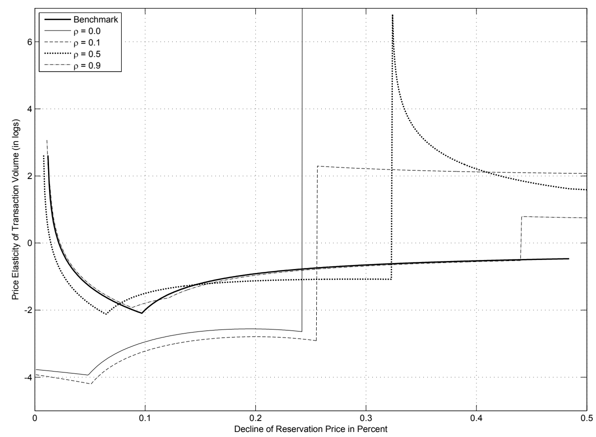
Figure A.1: Cross-segment competition. This figure characterises the optimal sales decision of homeowners in a heterogeneous market for varying levels of the cross-segment competition. Sections (a) to (d) exhibit different properties of the model: the share of withdrawn oversupply, price discounts, price elasticity and housing inventory. The respective properties are depicted on the vertical axis. The percentage decline in the reservation price is on the horizontal axis. For details on the parameterization please confer to Table A.1 in the appendix.



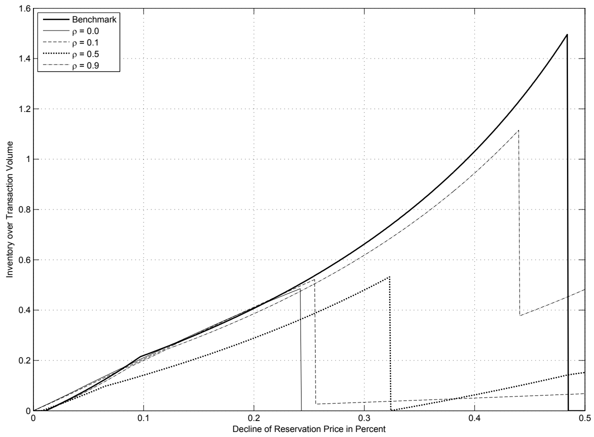
(a) Share of withdrawn oversupply.



(b) Price discount vs. long-run house price.



(c) Price elasticity of home sales.



(d) Inventory over home sales.

Figure A.2: Shock co-movement. This figure characterises the optimal sales decision of homeowners in a heterogeneous market for varying levels of the shock co-movement. Sections (a) to (d) exhibit different properties of the model: the share of withdrawn oversupply, price discounts, price elasticity and housing inventory. The respective properties are depicted on the vertical axis. The percentage decline in the reservation price is on the horizontal axis. For details on the parameterization please confer to Table A.1 in the appendix.

Appendix B

Hedge Funds and Prime Brokers

Consolidation Process of Hedge Fund Data

In general, hedge funds are not required to disclose any performance information. For marketing reasons, however, they often choose to provide such information to one or more private data providers. Each of these databases covers merely a portion of the entire hedge fund universe. Hence, there is a need to merge data from different sources. At the same time, one hedge fund might appear in several databases. Thus, a structured consolidation process is needed to identify and remove duplicates.

In our case, data stems from four different databases: Barclayhedge, Eurekahedge, Hedge Fund Research, TASS. Since we are interested in the most systemically relevant funds, we identify the 100 largest global active hedge funds by AuM in each database as of December 2011. Based-on this pre-selection, we proceed in three steps similar to Patton and Ramadorai (2013) and Joenvaara et al. (2012).

1. Management companies: We detect the name of the management company behind each reported hedge fund. Next, we delete punctuations, spaces as well as filler words that do not yield essential information (e.g. 'LLC', 'Fund'). Then, by grouping all funds related to the same management company, we identify 206 fund families.

2. De-duplication: To identify duplicates, we compare the performance data of all hedge funds within each fund family. For this, we apply the metric proposed in Joenvaara et al. (2012) and allow for a 10% tolerance. In addition, we employ a statistic based on the median absolute deviation between the records of two funds. Both procedures yield the same conclusions.

3. Selection: To create a unique data entry for the identified hedge fund duplicates, we first select the record with the longest available time horizon. Any missing values in hedge fund performance are then filled in using the information provided by the

duplicates. The same applies to administrative information, especially prime broker relations. Moreover, we require 12 months of consecutive reported fund performance. As a result, we detect 306 unique hedge funds.

Details of Prime Brokers

The table below reports all prime brokers considered in the calculations. We observe 21 active relations. Due to unavailability of stock market data five relations are excluded from the calculations (Banco BTG, Fortis, LaSalle, Man Group, MF Global). Moreover, for representativeness considerations we add those major prime brokers to the sample that merged or collapsed in the wake of the 2007-2008 financial crisis (Bear Stearns, Lehman Brothers, Merrill Lynch). At last, Newedge, a joint venture of Credit Agricole and Societe Generale, is replaced by its parent companies. Thus, there are finally 20 constituents.

Table B.1: Prime broker details. This table contains the names and accumulated mandates of prime brokers linked to hedge funds in our dataset, and whether they are excluded from the calculations. Also included are two different weight measures (uniform and mandate-weighted).

Prime Broker	Identified Relations	Reported Mandates	Added	Excluded	Uniform Weight (in %)	Mandates as Weight (in %)
AIG	Yes	1			5.0	0.5
Banco BTG	Yes	1		Yes		
Bank of America Merrill Lynch	Yes	5			5.0	2.5
Barclays	Yes	9			5.0	4.5
Bear Stearns			Yes		5.0	NA
BNP Paribas	Yes	6			5.0	3.0
Citigroup	Yes	10			5.0	5.0
Credit Suisse	Yes	17			5.0	8.5
Deutsche Bank	Yes	13			5.0	6.5
Fortis	Yes	4		Yes		
Goldman Sachs	Yes	38			5.0	19.0
JP Morgan	Yes	34			5.0	17.0
LaSalle	Yes	1		Yes		
Lehman Brothers			Yes		5.0	NA
Man Group	Yes	1		Yes		
Merrill Lynch			Yes		5.0	NA
MF Global	Yes	1		Yes		
Morgan Stanley	Yes	22			5.0	11.0
Newedge (Joint Venture):	Yes	(13)				
Credit Agricole		6.5			5.0	3.3
Societe Generale		6.5			5.0	3.3
Nomura	Yes	1			5.0	0.5
Royal Bank of Scotland	Yes	2			5.0	1.0
SEB	Yes	17			5.0	8.5
Swedbank	Yes	1			5.0	0.5
UBS	Yes	11			5.0	5.5
Total	21	210	3	5	100.0	100.0

Please note that merely 45% of all funds actually report any values. Nonetheless, we are confident that our selection is highly representative for the set of active prime brokers, since most identified prime brokers account for at least more than one mandate.

Table B.2: Variable definitions and sources. This table contains the names, data sources, brief descriptions and previous use in the literature of each variable.

Variable	Data Source	Description	Use in the Literature
PBER	Bloomberg, Datastream	The excess return of banks attributable to prime brokerage calculated as the residual from a regression of a prime broker index return on a general bank index return.	Boyson et al. (2010)
HFILLIQ	Barclayhedge, Eurekahedge, Hedge Fund Research, Lipper TASS	The proportion of aggregated returns of the largest global hedge funds attributable to portfolio liquidity. It is computed as the residual from a regression of aggregated hedge fund returns on five lookback straddles, a put option proxy and a constant.	Agarwal and Naik (2004), Boyson et al. (2010), Fung and Hsieh (2001)
NETPOS	Federal Reserve Bank of New York	The net position of primary dealers registered with the Federal Reserve Bank of New York.	Adrian and Fleming (2005)
FINANCING	Federal Reserve Bank of New York	The overnight net financing of primary dealers registered with the Federal Reserve Bank of New York.	Adrian and Fleming (2005)
LENDING	Federal Reserve Bank of New York	The term net financing of primary dealers registered with the Federal Reserve Bank of New York.	Adrian and Fleming (2005)
BOND	Barclays	The monthly return of the Barclay's global aggregate bond index.	Boyson et al. (2010)
CURRENCY	Federal Reserve Board	The monthly return of the US dollar exchange rate vis-a-vis the Euro.	Boyson et al. (2010)
DEFRISK	Moody's	The monthly return of the credit spread between Moody's Baa yield and the 10-year constant maturity US government bond yield.	Fama and French (1993), Fung and Hsieh (2001), Longstaff et al. (2005)
EQUITY	MSCI	The yearly return of the global equity market.	Fung and Hsieh (1997)
GOLD	London Gold Bullion	The yearly return of the gold spot price.	Fung and Hsieh (1997)
HOUSE	Standard & Poors	The monthly growth of the S&P Case/Shiller 20-city composite house price index.	NA
HOUSETREND	Standard & Poors	The fraction of yearly house price growth not explained by monthly growth. It is computed as the residual from a regression of the yearly growth on the monthly growth.	NA
LIQRISK	British Bankers Association, Federal Reserve Bank of New York	The growth of the TED spread computed as the difference between the 3-month USD-Libor and the 3-month US treasury bill yield.	Campbell (2003), Taylor and Williams (2009)
OIL	International Commodities Exchange	The yearly return of the Brent oil price index.	NA
Fund flows	Barclayhedge, Eurekahedge, Hedge Fund Research, TASS	The difference between realised AuM and approximated AuM. The approximation involves past realised AuM adjusted by contemporaneous performance.	Boyson et al. (2010), Fung et al. (2008), Getmansky (2012)
Global bank index return	Datastream	The monthly return of a broad-based global bank index.	Chan et al. (2006), Boyson et al. (2010)
Asset-based strategy factors	David Hsieh	Lookback option straddles on bonds, commodities, currencies, equities and interest rates	Fung and Hsieh (2001)
MSCI put option	MSCI, own calculations	The negative portion of the monthly MSCI percentage change.	Agarwal and Naik (2004), Boyson et al. (2010)

Appendix C

Financial Sector Integration

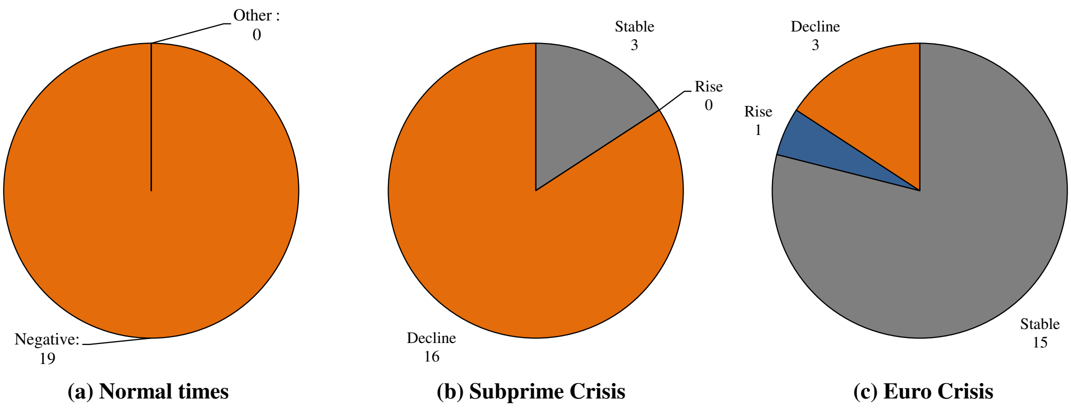


Figure C.1: Auxiliary regressions. This figure summarises the frequency and direction of relations between the residual US excess return and the domestic factors of the other $i-1$ countries in (a) normal times, (b) the Subprime Crisis, (c) the Euro Crisis. The evidence is based on country-specific auxiliary regressions to the three-factor capital asset pricing model. Detailed regression results are presented in Table C.4 in the appendix.

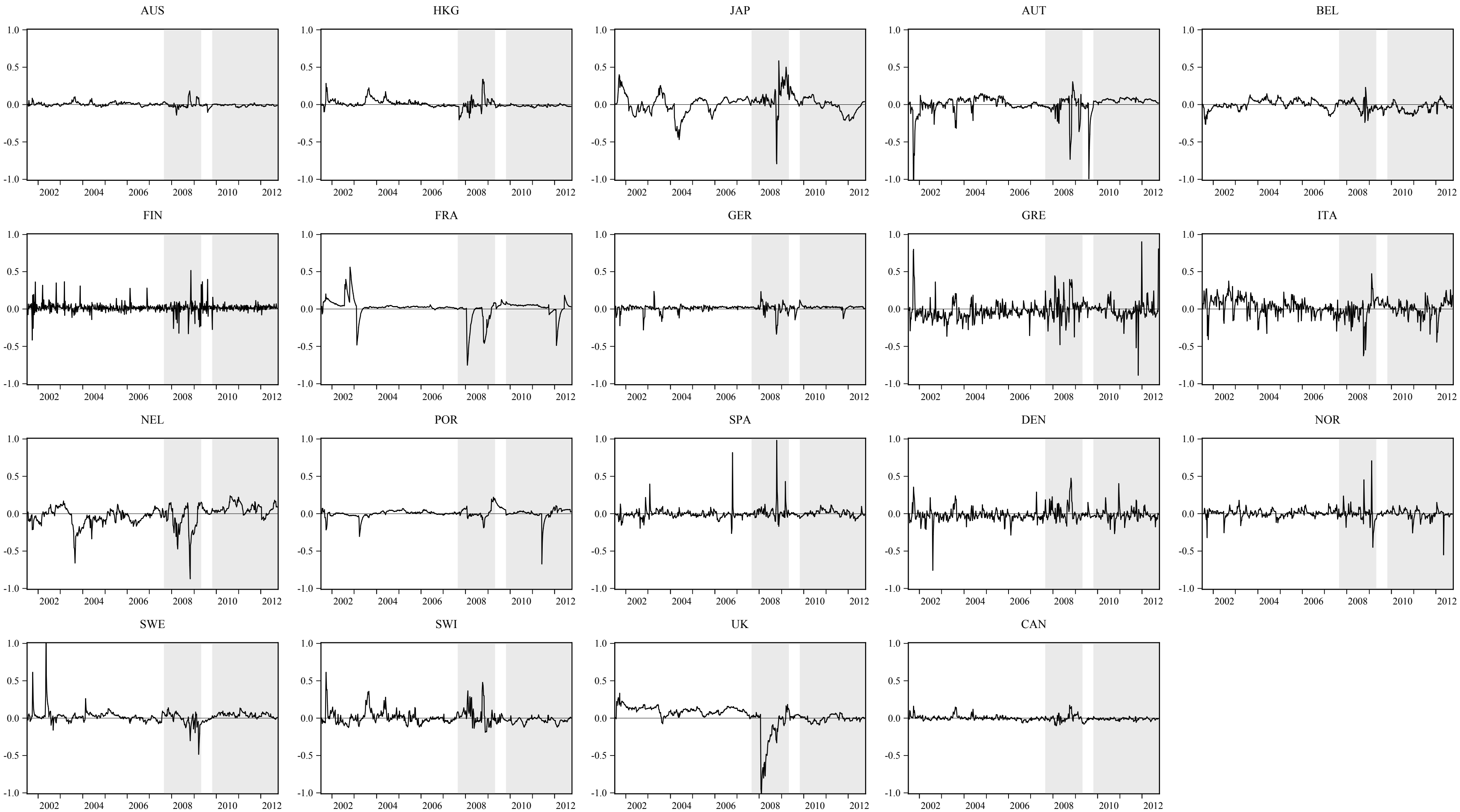


Figure C.2: DCCX vs. DCC correlations. This figure shows the time-varying residual correlation of the US financial sector vis-a-vis its respective domestic equivalents between July 4, 2001 and September 26, 2012 after subtracting the DCC-implied correlation from the DCCX correlation. The resulting correlation differential informs about the contribution extreme news shocks and repo failures make over and above the standard DCC model. The left (right) grey-shaded area denotes the Subprime Crisis (Euro Crisis).

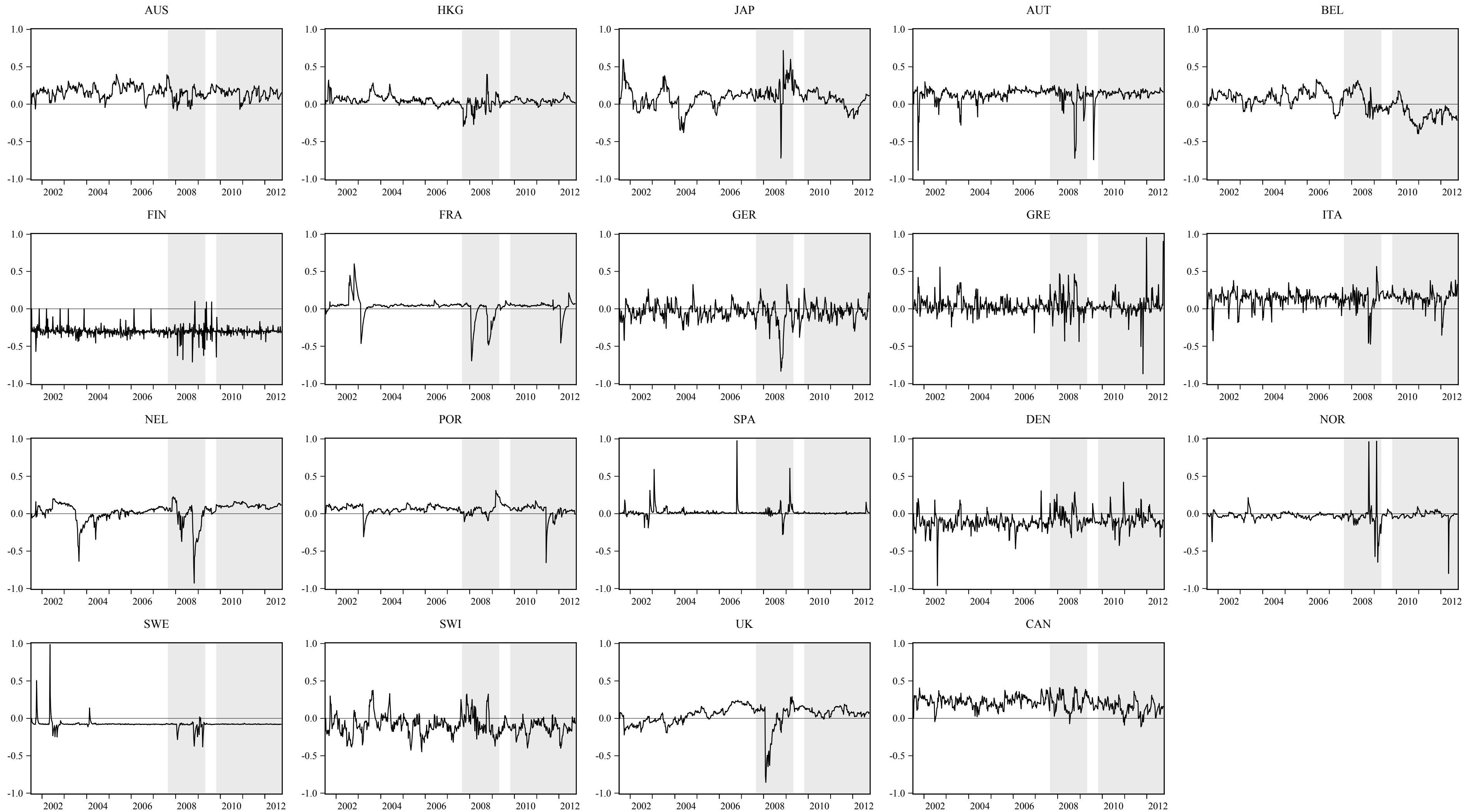


Figure C.3: DCCX-implied residual correlations. This figure shows the DCCX-implied time-varying residual correlations of the US financial sector vis-a-vis its respective domestic equivalents between July 4, 2001 and September 26, 2012. The left (right) grey-shaded area denotes the Subprime Crisis (Euro Crisis).

Table C.1: Variables and sources. This table reports on variables and data sources. Note that *i* is chosen in accordance with the subindices throughout the paper.

							Dependent		External	
Benchmark	**i**	**Country**	**Market Type**	**Source***	**Return Type**	**N**	**Index**	**Ticker**	**Index**	**Ticker**
USA	0	United States	Equity Indices	MSCI	MSRI	587	Financials	M1USFN$		
Comparables										
AUS	1	Australia	Equity Indices	MSCI	MSRI	587	Financials	M1AUFN$	Country	MSAUST$
AUT	2	Austria	Equity Indices	MSCI	MSRI	587	Financials	M1ATFN$	Country	MSASTR$
BEL	3	Belgium	Equity Indices	MSCI	MSRI	587	Financials	M1BEFN$	Country	MSBELG$
CAN	4	Canada	Equity Indices	MSCI	MSRI	587	Financials	M1CAFN$	Country	MSCNDA$
DEN	5	Denmark	Equity Indices	MSCI	MSRI	587	Financials	M1DKFN$	Country	MSDNMK$
FIN	6	Finland	Equity Indices	MSCI	MSRI	587	Financials	M1FIFN$	Country	MSFIND$
FRA	7	France	Equity Indices	MSCI	MSRI	587	Financials	M1FRFN$	Country	MSFRNC$
GER	8	Germany	Equity Indices	MSCI	MSRI	587	Financials	M1DEFN$	Country	MSGERM$
GRE	9	Greece	Equity Indices	MSCI	MSRI	587	Financials	M1GDFN$	Country	MSGDEE$
HKG	10	Hongkong	Equity Indices	MSCI	MSRI	587	Financials	M1HKFN$	Country	MSHGKG$
ITA	11	Italy	Equity Indices	MSCI	MSRI	587	Financials	M1ITFN$	Country	MSITAL$
JAP	12	Japan	Equity Indices	MSCI	MSRI	587	Financials	M1JPFN$	Country	MSJPAN$
NEL	13	Netherlands	Equity Indices	MSCI	MSRI	587	Financials	M1NLFN$	Country	MSNETH$
NOR	14	Norway	Equity Indices	MSCI	MSRI	587	Financials	M1NOFN$	Country	MSNWAY$
POR	15	Portugal	Equity Indices	MSCI	MSRI	587	Financials	M1PTFN$	Country	MSPORD$
SPA	16	Spain	Equity Indices	MSCI	MSRI	587	Financials	M1ESFN$	Country	MSSPAN$
SWE	17	Sweden	Equity Indices	MSCI	MSRI	587	Financials	M1SEFN$	Country	MSSWDN$
SWI	18	Switzerland	Equity Indices	MSCI	MSRI	587	Financials	M1CHFN$	Country	MSSWIT$
UK	19	United Kingdom	Equity Indices	MSCI	MSRI	587	Financials	M1UKFN$	Country	MSUTDK$
Global Factors										
G		Global	Equity Indices	MSCI	MSRI	587			Financials	M1DWFN$
US		United States	Equity Indices	MSCI	MSRI	587			Country	MSUSAM$
Other Data										
LIBOR		United States	Interest Rates	BBA		587			Country	BBUSD1W
Repo failures		United States	Other	FRBNY		587			Country	

* MSCI = Morgan Stanley Capital International, BBA = Britisch Bankers Association, FRNBY = Federal Reserve Bank of New York

Table C.2: Data characteristics. This table portrays various characteristics of the used variables. Descriptive statistics include the mean, median, minimum, maximum and standard deviation. The skewness, kurtosis and p-values of the Jarque-Bera statistics are reported to test for normality. The p-values of the Ljung-Box test statistics (LB(q)) give indicative information on serial correlation up to order q. Assessments of individual and joint stationarity are based on p-values of the Augmented-Dickey Fuller (ADF). The correlations illustrate co-movement patterns vis-a-vis the US financial sector excess performance in normal times and during the Subprime Crisis and Euro Crisis.

Panel A: Financial Sector Excess Returns

	.... Asia/Pacific			.... Euro						
Descriptive Stats	AUS	HKG	JAP	AUT	BEL	FIN	FRA	GER	GRE	ITA
Mean	0.189	0.169	-0.085	0.028	-0.192	0.296	0.003	-0.095	-0.448	-0.166
Median	0.504	0.154	-0.200	0.461	0.454	0.438	0.347	0.351	-0.004	0.173
Max	16.270	15.993	20.750	27.263	22.488	13.441	27.189	23.958	32.660	18.178
Min	-22.484	-18.303	-20.995	-33.286	-44.337	-19.285	-24.235	-20.796	-31.240	-18.620
Std. dev.	3.801	3.690	4.439	5.892	5.919	4.054	5.749	5.334	6.468	5.065
Normality (Jarque-Bera)										
Skewness	-0.677	-0.023	-0.162	-0.948	-1.137	-0.636	-0.097	-0.413	-0.434	-0.153
Kurtosis	8.152	5.902	5.322	8.649	10.598	5.421	5.865	5.933	6.452	4.986
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Autocorrelation (Ljung-Box)										
LB(1)	0.142	0.271	0.145	0.369	0.396	0.015	0.000	0.004	0.041	0.060
LB(2)	0.219	0.285	0.125	0.240	0.034	0.039	0.000	0.002	0.119	0.046
LB(3)	0.009	0.014	0.026	0.000	0.071	0.019	0.000	0.001	0.000	0.001
Stationarity (Augmented Dickey-Fuller)										
ADF	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Correlations vis-a-vis the US financial sector										
Whole sample	0.645	0.545	0.391	0.656	0.653	0.601	0.741	0.704	0.421	0.657
Subprime Crisis	0.690	0.614	0.569	0.708	0.600	0.647	0.770	0.722	0.586	0.708
Euro Crisis	0.720	0.574	0.471	0.751	0.735	0.738	0.768	0.773	0.319	0.671
Observations	586	586	586	586	586	586	586	586	586	586

	...... Euro			...... Non-Euro					North America	
Descriptive Stats	NEL	POR	SPA	DEN	NOR	SWE	SWI	UK	CAN	US
Mean	-0.136	-0.386	0.005	0.051	0.175	0.146	-0.043	-0.065	0.191	-0.082
Median	0.308	-0.046	0.158	0.400	0.704	0.364	0.192	0.071	0.402	0.103
Max	33.108	28.000	19.728	20.547	34.333	18.825	20.974	20.284	13.021	22.303
Min	-30.637	-23.410	-24.815	-26.515	-35.352	-27.883	-22.263	-26.405	-17.307	-27.228
Std. dev.	7.149	5.143	5.196	4.714	6.051	4.952	4.977	4.513	3.295	4.065
Normality (Jarque-Bera)										
Skewness	-0.428	-0.069	-0.165	-0.585	-0.833	-0.638	-0.375	-0.495	-0.335	-0.520
Kurtosis	7.527	7.508	5.080	7.083	10.863	6.849	6.525	8.170	6.496	11.004
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Autocorrelation (Ljung-Box)										
LB(1)	0.016	0.820	0.174	0.001	0.003	0.000	0.000	0.005	0.127	0.000
LB(2)	0.043	0.794	0.395	0.003	0.012	0.000	0.000	0.019	0.308	0.000
LB(3)	0.001	0.012	0.203	0.000	0.000	0.000	0.000	0.009	0.270	0.000
Stationarity (Augmented Dickey-Fuller)										
ADF	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Correlations vis-a-vis the US financial sector										
Whole sample	0.679	0.402	0.644	0.564	0.614	0.677	0.760	0.778	0.783	1.000
Subprime Crisis	0.604	0.586	0.689	0.653	0.686	0.697	0.800	0.784	0.780	1.000
Euro Crisis	0.743	0.399	0.645	0.540	0.691	0.767	0.769	0.815	0.824	1.000
Observations	586	586	586	586	586	586	586	586	586	586

Table C.2 continued

Panel B: Domestic and Global Factors, and Unexpected Repo Market Failures											
	.... **Asia/Pacific**			.... **Euro**							
Descriptive Stats	AUS	HKG	JAP	AUT	BEL	FIN	FRA	GER	GRE	ITA	NEL
Mean	0.240	0.157	0.028	0.113	0.083	-0.043	0.052	0.081	-0.191	0.011	0.051
Median	0.369	0.145	0.125	0.221	0.228	0.099	0.104	0.120	0.304	0.118	0.095
Max	8.303	8.636	8.749	10.895	6.344	13.599	8.484	7.923	12.602	10.814	7.751
Min	-9.577	-10.088	-7.852	-15.454	-20.993	-19.077	-8.986	-11.711	-16.606	-8.551	-9.173
Std. dev.	2.177	2.294	2.256	2.700	2.279	3.340	1.821	2.040	3.683	2.106	1.868
Normality (Jarque-Bera)											
Skewness	-0.362	-0.073	-0.043	-0.734	-1.966	-0.428	-0.118	-0.611	-0.506	0.089	-0.479
Kurtosis	4.448	5.047	3.985	5.969	17.682	6.795	6.064	6.928	4.750	5.556	6.389
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Autocorrelation (Ljung-Box)											
LB(1)	0.004	0.273	0.068	0.833	0.495	0.017	0.000	0.000	0.763	0.022	0.002
LB(2)	0.015	0.506	0.173	0.945	0.701	0.048	0.000	0.001	0.562	0.064	0.002
LB(3)	0.006	0.706	0.310	0.406	0.688	0.107	0.000	0.003	0.401	0.057	0.005
Stationarity (Augmented Dickey-Fuller)											
ADF	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Correlations vis-a-vis the US financial sector											
Whole sample	-0.148	-0.111	-0.131	-0.127	-0.169	-0.113	-0.222	-0.212	-0.124	-0.205	-0.225
Subprime Crisis	-0.152	-0.189	-0.187	-0.203	-0.292	-0.414	-0.598	-0.553	-0.356	-0.525	-0.606
Euro Crisis	0.199	0.005	-0.043	0.439	-0.115	0.164	0.320	0.149	0.138	0.382	0.060
Observations	586	586	586	586	586	586	586	586	586	586	586

	.... **Euro**		.... **Non-Euro**					**North America**		**Global**	**Repo**
Descriptive Stats	SPA	POR	DEN	NOR	SWE	SWI	UK	CAN	US		**Fails**
Mean	0.063	0.119	0.206	0.212	0.159	0.140	0.080	0.153	0.066	-0.075	0.000
Median	0.077	0.144	0.346	0.373	0.159	0.112	0.035	0.265	0.208	-0.074	-0.006
Max	10.208	9.183	9.199	15.332	8.829	5.799	7.793	5.612	10.365	8.817	0.568
Min	-10.348	-10.374	-11.911	-14.881	-11.790	-7.086	-7.173	-7.140	-16.672	-11.825	-0.243
Std. dev.	2.507	2.361	2.249	3.254	2.489	1.621	1.546	1.841	2.560	1.804	0.059
Normality (Jarque-Bera)											
Skewness	-0.284	0.021	-0.431	-0.505	-0.355	-0.143	0.229	-0.496	-0.671	-0.414	3.049
Kurtosis	5.141	5.088	5.368	6.245	5.720	4.280	6.135	4.403	8.225	11.132	28.805
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Autocorrelation (Ljung-Box)											
LB(1)	0.000	0.135	0.007	0.019	0.000	0.000	0.013	0.163	0.066	0.003	0.032
LB(2)	0.001	0.307	0.009	0.008	0.000	0.000	0.000	0.374	0.183	0.001	0.068
LB(3)	0.002	0.486	0.006	0.009	0.000	0.000	0.000	0.241	0.225	0.000	0.115
Stationarity (Augmented Dickey-Fuller)											
ADF	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Correlations vis-a-vis the US financial sector											
Whole sample	-0.120	-0.192	-0.159	-0.156	-0.162	-0.159	-0.192	-0.127	0.880	0.325	0.044
Subprime Crisis	-0.257	-0.518	-0.245	-0.181	-0.431	-0.504	-0.363	-0.188	0.863	0.512	0.126
Euro Crisis	0.268	0.242	0.070	0.203	0.025	-0.001	0.138	0.041	0.939	0.181	0.023
Observations	586	586	586	586	586	586	586	586	586	586	586

Table C.3: Individual three-factor asset pricing model. The table shows the estimates of the three-factor pricing model of Bekaert et al. (2014):

$$R_{it} = E_{t-1}[R_{it}] + \beta_i^{'} F_t + \gamma_i^{'} CR_1 F_t + \eta_i^{'} CR_2 F_t + \lambda_i CR_1 + \tau_i CR_2 + \epsilon_{it}.$$

The t-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust (Newey and West, 1987). LB (LB^2) denotes the p-value of a Ljung-Box test on one period-lagged serial correlation (heteroscedasticity) in the residuals. *** (**, *) indicates statistical significance at the 1% (5%, 10%) level.

	.... Asia/Pacific			.... Euro area						
Expectations	AUS	HKG	JAP	AUT	BEL	FIN	FRA	GER	GRE	ITA
Div. Yield	0.005	-0.005	-0.153*	0.121	-0.054***	0.020	-0.011	-0.050	-0.010	-0.031
	(0.49)	(-0.38)	(-1.67)	(1.23)	(-3.45)	(1.62)	(-0.59)	(-0.98)	(-0.48)	(-1.46)
AR(1)	-0.129**	0.003	-0.134**	-0.104*	-0.193*	-0.119**	-0.168***	-0.106	-0.097	-0.052
	(-2.40)	(0.06)	(-2.44)	(-1.81)	(-1.89)	(-2.19)	(-2.57)	(-1.52)	(-1.39)	(-1.06)
Domestic factor										
Total	0.941***	1.170***	1.412***	0.945***	1.220***	0.174***	0.916***	1.117***	1.232***	0.932***
	(24.89)	(34.53)	(29.67)	(12.92)	(30.17)	(3.69)	(13.57)	(17.72)	(42.87)	(21.21)
Subprime crisis	-0.158**	-0.025	-0.190	0.095	0.205	0.397***	-0.447**	-0.330**	-0.058	-0.025
	(-2.44)	(-0.55)	(-1.48)	(0.60)	(1.38)	(3.46)	(-2.40)	(-2.37)	(-1.16)	(-0.36)
Euro crisis	0.092*	-0.042	-0.300***	0.240**	-0.555***	0.199**	0.257**	-0.299***	0.015	0.658***
	(1.74)	(-1.10)	(-4.29)	(1.97)	(-4.95)	(2.16)	(2.30)	(-3.43)	(0.08)	(6.55)
Global factor										
Total	0.833***	0.586***	1.064***	1.469***	1.238***	1.062***	1.445***	1.236***	1.380***	1.287***
	(16.49)	(9.04)	(13.12)	(10.56)	(20.58)	(6.73)	(20.67)	(10.23)	(20.27)	(26.26)
Subprime crisis	0.270***	0.164**	0.376***	0.149	0.185	-0.170	0.114	0.146	0.162**	0.054
	(2.99)	(2.30)	(3.04)	(0.77)	(1.31)	(-0.78)	(1.10)	(1.02)	(2.12)	(0.63)
Euro crisis	0.089	0.026	-0.030	0.081	0.996***	0.129	0.559***	0.454***	0.206	0.116
	(1.02)	(0.36)	(-0.24)	(0.43)	(5.69)	(0.68)	(3.54)	(2.96)	(0.66)	(0.87)
US factor										
Total	0.891***	0.837***	0.546***	1.252***	1.532***	0.872***	1.761***	1.599***	1.171***	1.397***
	(23.02)	(46.62)	(12.04)	(13.62)	(33.97)	(9.57)	(20.46)	(18.31)	(29.22)	(26.15)
Subprime crisis	0.050	0.028	0.032	0.341***	0.079	0.196	-0.375***	-0.163	-0.060	-0.217***
	(0.80)	(0.87)	(0.36)	(2.54)	(0.95)	(1.58)	(-3.08)	(-1.45)	(-1.04)	(-3.00)
Euro crisis	0.067	-0.073***	0.018	-0.045	0.114	0.271**	-0.138	-0.201**	-0.465***	-0.293***
	(1.37)	(-2.88)	(0.31)	(-0.39)	(1.10)	(2.51)	(-1.19)	(-1.96)	(-2.58)	(-3.68)
Regime Shifts										
Subprime crisis	-0.104	0.131	0.354	-0.396	0.249	0.085	0.260	0.394	-0.186	0.117
	(-0.62)	(1.20)	(1.62)	(-1.24)	(1.47)	(0.34)	(1.26)	(1.45)	(-0.90)	(0.74)
Euro crisis	0.021	-0.006	0.492	-0.163	-0.003	0.304**	0.109	0.251	-0.298	-0.048
	(0.22)	(-0.10)	(1.89)	(-0.73)	(-0.02)	(2.43)	(0.78)	(1.11)	(-0.67)	(-0.40)
LB	0.209	0.977	0.670	0.021	0.338	0.877	0.389	0.007	0.204	0.810
LB^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adj. R-squared	0.911	0.962	0.827	0.845	0.913	0.640	0.902	0.892	0.831	0.929

Table C.3 continued

Expectations	NEL	POR	SPA	DEN	NOR	SWE	SWI	UK	CAN	USA
	.... **Euro area**			.... **Non-Euro area**					... **North America** ...	
Div. Yield	-0.013	-0.008	-0.020	-0.013	0.011	-0.021	**-0.090*** **	-0.004	**0.045** **	**-0.044** **
	(-0.49)	(-0.22)	(-1.04)	(-0.40)	(0.27)	(-0.75)	**(-2.81)**	(-0.19)	**(2.15)**	**(-2.24)**
AR(1)	-0.035	**-0.105***	-0.068	-0.061	-0.079	**-0.114** **	**-0.199** **	-0.058	-0.052	**-0.221*** **
	(-0.66)	**(-1.81)**	(-1.43)	(-1.27)	(-1.46)	**(-2.14)**	**(-2.46)**	(-0.70)	(-1.34)	**(-4.02)**
Domestic factor										
Total	**1.064*** **	**1.045*** **	**1.131*** **	**0.839*** **	**0.764*** **	**0.877*** **	**0.934*** **	**0.727*** **	**0.657*** **	
	(9.53)	**(9.52)**	**(17.49)**	**(13.52)**	**(10.84)**	**(14.96)**	**(13.49)**	**(10.90)**	**(12.00)**	
Subprime crisis	**0.616** **	-0.271	-0.113	-0.044	-0.002	0.071	**-0.488*** **	0.100	-0.132	
	(2.43)	(-1.57)	(-1.24)	(-0.36)	(-0.02)	(0.53)	**(-3.65)**	(0.56)	(-1.03)	
Euro crisis	0.298	**0.302***	**0.134***	0.149	**0.237** **	-0.002	**-0.281*** **	0.030	-0.090	
	(1.46)	**(1.66)**	**(1.84)**	(0.85)	**(2.08)**	(-0.03)	**(-2.87)**	(0.30)	(-1.10)	
Global factor										
Total	**1.929*** **	**0.942*** **	**1.288*** **	**0.956*** **	**0.996*** **	**1.117*** **	**1.319*** **	**1.166*** **	**0.571*** **	**0.658*** **
	(12.14)	**(8.28)**	**(19.49)**	**(7.61)**	**(9.14)**	**(13.34)**	**(11.29)**	**(11.78)**	**(9.46)**	**(5.30)**
Subprime crisis	0.404	0.023	0.111	**0.326***	**0.906*** **	-0.029	0.033	0.211	**0.217** **	0.148
	(1.34)	(0.15)	(1.30)	**(1.69)**	**(3.52)**	(-0.20)	(0.23)	(1.04)	**(2.10)**	(0.98)
Euro crisis	0.060	**1.109*** **	-0.002	**0.651** **	0.233	0.070	**0.335** **	0.177	-0.073	-0.195
	(0.27)	**(4.20)**	(-0.02)	**(2.44)**	(1.16)	(0.59)	**(2.21)**	(1.39)	(-0.75)	(-1.45)
US factor										
Total	**1.968*** **	**0.755*** **	**1.456*** **	**1.005*** **	**1.213*** **	**1.381*** **	**1.558*** **	**1.248*** **	**0.967*** **	**1.306*** **
	(20.93)	**(10.06)**	**(17.00)**	**(14.60)**	**(15.18)**	**(24.24)**	**(22.27)**	**(23.83)**	**(24.20)**	**(24.73)**
Subprime crisis	-0.161	-0.027	-0.151	-0.051	**0.283** **	-0.044	**-0.217***	0.105	-0.027	**0.192** **
	(-0.91)	(-0.25)	(-1.22)	(-0.48)	**(2.06)**	(-0.44)	**(-1.82)**	(1.31)	(-0.19)	**(2.18)**
Euro crisis	0.061	-0.105	**-0.295*** **	0.069	0.081	0.035	**-0.292*** **	0.029	0.034	-0.031
	(0.47)	(-0.53)	**(-3.15)**	(0.42)	(0.80)	(0.49)	**(-3.65)**	(0.45)	(0.55)	(-0.49)
Regime Shifts										
Subprime crisis	0.093	**-0.835** **	0.093	-0.341	0.183	0.119	**0.457***	-0.265	-0.211	0.086
	(0.23)	**(-2.35)**	(0.57)	(-1.45)	(0.45)	(0.43)	**(1.70)**	(-1.03)	(-0.72)	(0.36)
Euro crisis	-0.169	-0.514	0.151	-0.152	0.028	0.162	**0.252***	-0.028	-0.114	-0.026
	(-0.86)	(-1.49)	(0.93)	(-0.69)	(0.13)	(1.23)	**(1.76)**	(-0.25)	(-0.98)	(-0.32)
LB	0.492	0.017	0.932	0.248	0.394	0.916	0.734	0.008	0.251	0.799
LB^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adj. R-squared	0.857	0.629	0.936	0.711	0.751	0.871	0.893	0.893	0.827	0.890

Table C.4: Auxiliary regressions. The table shows country-specific auxiliary regressions of the US residual derived from the US three-factor model on the respective domestic factor according to equation [4]:

$$\epsilon_{0t} = (\beta_i + \gamma_i CR_1 + \eta_i CR_2) f^D_{it} + \epsilon_{0it}.$$

t-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust (Newey and West, 1987). LB (LB^2) denotes the p-value of a Ljung-Box test on one period-lagged serial correlation (heteroscedasticity) in the residuals. *** (**, *) indicates statistical significance at the 1% (5%, 10%) level.

	Asia/Pacific			**Euro area**						
	AUS	HKG	JAP	AUT	BEL	FIN	FRA	GER	GRE	ITA
Total	**-0.185****	**-0.154****	**-0.189****	**-0.087****	**-0.219****	**-0.360****	**-0.053****	**-0.315****	**-0.133****	**-0.319****
	(-5.80)	**(-4.79)**	**(-5.89)**	**(-2.27)**	**(-5.00)**	**(-7.01)**	**(-2.43)**	**(-7.06)**	**(-5.96)**	**(-5.95)**
Subprime crisis	**-0.208*****	**-0.187*****	**-0.249****	**-0.303*****	**-0.119***	**-0.203***	**-0.270*****	-0.142	**-0.228*****	**-0.195****
	(-2.67)	**(-2.65)**	**(-2.42)**	**(-5.63)**	**(-1.84)**	**(-1.85)**	**(-4.69)**	(-1.63)	**(-3.86)**	**(-2.48)**
Euro crisis	-0.029	0.080	0.047	-0.038	-0.029	0.056	-0.019	0.027	**0.105*****	**0.144****
	(-0.71)	(1.55)	(0.92)	(-0.77)	(-0.46)	(0.85)	(-0.47)	(0.43)	**(3.85)**	**(2.35)**
LB	0.982	0.137	0.266	0.200	0.329	0.852	0.014	0.751	0.019	0.759
LB^2	0.000	0.000	0.000	0.001	0.021	0.000	0.000	0.000	0.000	0.000
Adj. R-squared	0.215	0.132	0.178	0.216	0.232	0.337	0.140	0.315	0.223	0.320

	Euro area			**Non-Euro area**					**North America**
	NEL	POR	SPA	DEN	NOR	SWE	SWI	UK	CAN
Total	**-0.308****	**-0.141****	**-0.307****	**-0.188****	**-0.108****	**-0.166****	**-0.265****	**-0.338****	**-0.125****
	(-5.93)	**(-3.48)**	**(-6.15)**	**(-5.83)**	**(-5.16)**	**(-5.33)**	**(-5.01)**	**(-6.55)**	**(-3.73)**
Subprime crisis	**-0.334*****	-0.157	**-0.140***	**-0.253*****	**-0.171*****	**-0.244*****	-0.232	**-0.302****	**-0.369*****
	(-3.69)	(-1.53)	**(-1.65)**	**(-3.77)**	**(-3.44)**	**(-2.74)**	(-1.49)	**(-2.04)**	**(-6.19)**
Euro crisis	-0.034	0.038	**0.182*****	0.017	**-0.065***	-0.035	0.018	-0.062	0.011
	(-0.52)	(0.73)	**(3.24)**	(0.31)	**(-1.74)**	(-0.66)	(0.24)	(-0.75)	(0.18)
LB	0.930	0.079	0.348	0.509	0.411	0.083	0.952	0.666	0.816
LB^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.008
Adj. R-squared	0.382	0.126	0.290	0.248	0.250	0.229	0.166	0.311	0.193

Table C.5: Residual variances. The table shows parameter estimates of time-varying variances of the respective (country-specific) US residuals and domestic residuals. The variances follow a GARCH(1,1) process:

$$h_{it} = \omega_i + \delta_i \epsilon_{it-1}^2 + \theta_i h_{it-1}^2.$$

t-statistics are reported in parentheses. Standard errors are heteroskedasticity robust (Bollerslev and Wooldridge, 1992). *** (**, *) indicates statistical significance at the 1% (5%, 10%) level.

Panel A: US residuals (country-specific)

	Asia/Pacific			Euro area						
	AUS	HKG	JAP	AUT	BEL	FIN	FRA	GER	GRE	ITA
Constant	0.020*	0.023*	0.016	0.022*	0.014**	0.019*	0.019	0.014*	0.014	0.018*
	(1.78)	(1.69)	(1.48)	(1.90)	(1.98)	(1.69)	(1.59)	(1.68)	(1.61)	(1.68)
δ	0.110***	0.100***	0.098***	0.098***	0.083***	0.137***	0.090***	0.118***	0.079***	0.117***
	(3.19)	(3.07)	(3.06)	(3.01)	(3.06)	(3.07)	(3.03)	(3.26)	(3.13)	(3.22)
θ	0.872***	0.882***	0.890***	0.883***	0.903***	0.849***	0.895***	0.871***	0.908***	0.870***
	(25.98)	(29.95)	(29.44)	(28.25)	(36.27)	(19.69)	(30.19)	(26.45)	(40.50)	(23.73)

	Euro area			Non-Euro area				North America
	NEL	POR	SPA	DEN	NOR	SWE	SWI	UK	CAN
Constant	0.027*	0.022*	0.012*	0.014	0.024*	0.019**	0.021*	0.028**	0.021*
	(1.70)	(1.90)	(1.80)	(1.56)	(1.84)	(1.98)	(1.87)	(2.10)	(1.67)
δ	0.097***	0.092***	0.086***	0.097***	0.106***	0.101***	0.106***	0.168***	0.099**
	(2.82)	(2.58)	(3.23)	(2.76)	(3.55)	(3.26)	(2.58)	(2.72)	(2.55)
θ	0.875***	0.889***	0.903***	0.894***	0.874***	0.883***	0.876***	0.817***	0.887***
	(22.10)	(25.36)	(33.71)	(30.93)	(27.51)	(32.07)	(22.59)	(19.28)	(26.11)

Panel B: Domestic residuals

	Asia/Pacific			Euro area						
	AUS	HKG	JAP	AUT	BEL	FIN	FRA	GER	GRE	ITA
Constant	0.018	0.018**	0.053	0.119**	0.031	1.141**	0.054**	0.134**	0.021	0.022
	(1.58)	(2.28)	(1.47)	(2.06)	(1.50)	(2.30)	(2.10)	(2.00)	(0.87)	(1.52)
δ	0.064*	0.074**	0.081**	0.135***	0.170**	0.193***	0.095**	0.114**	0.116***	0.086***
	(1.94)	(2.36)	(3.53)	(3.77)	(2.30)	(2.85)	(2.38)	(2.55)	(2.72)	(3.33)
θ	0.917***	0.878***	0.902***	0.842***	0.839***	0.606***	0.891***	0.833***	0.893***	0.905***
	(25.27)	(24.03)	(34.15)	(21.99)	(15.17)	(4.66)	(23.40)	(16.23)	(28.37)	(34.26)

	Euro area			Non-Euro area				North America
	NEL	POR	SPA	DEN	NOR	SWE	SWI	UK	CAN
Constant	0.053	0.045	0.098	0.036	0.208*	0.045	0.053*	0.027**	0.046
	(1.17)	(1.37)	(1.33)	(1.19)	(1.93)	(1.57)	(1.88)	(1.97)	(1.63)
δ	0.096***	0.123***	0.086	0.087***	0.090***	0.087***	0.099***	0.105**	0.089**
	(3.27)	(4.24)	(1.60)	(4.27)	(3.27)	(3.74)	(3.78)	(4.11)	(2.50)
θ	0.901***	0.885***	0.859***	0.911***	0.880***	0.899***	0.880***	0.885***	0.885***
	(30.57)	(38.01)	(10.95)	(47.18)	(26.21)	(34.40)	(28.35)	(41.69)	(28.40)

Table C.6: Time-varying residual correlations. The table shows parameter estimates of dynamic conditional correlations. The correlation dynamics follow either a DCC(1,1) process (Engle, 2002),

$$q_{12t} = \rho_{12}(1-\alpha-\beta) + \alpha\xi_{1t-1}\xi_{2t-1} + \beta q_{12t-1}.$$

or a modified DCCX(1,1) process including asymmetries and external regressors:

$$q_{12t} = \rho_{12}(1-\alpha-\beta) + (\alpha + \phi_1 XTRM_{1t-1} + \phi_2 XTRM_{2t-1})\xi_{1t-1}\xi_{2t-1} + \beta q_{12t-1} + \phi_3 y_{t-1}.$$

t-statistics are reported in parentheses. Standard errors are asymptotic. *** (**, *) indicates statistical significance at the 1% (5%, 10%) level.

	Asia/Pacific			**Euro area**						
DCC(1,1)	AUS	HKG	JAP	AUT	BEL	FIN	FRA	GER	GRE	ITA
ρ	**0.161*** **	0.036	**0.077** **	**0.116** **	0.015	**-0.322*** **	0.018	-0.062	**0.062*** **	**0.123** **
	(3.13)	(1.08)	**(1.97)**	**(1.97)**	(0.13)	**(-9.15)**	(0.35)	(-1.16)	**(2.68)**	**(2.16)**
α	0.039	-0.014	-0.018	0.023	0.018	0.016	0.005	**0.096*** **	-0.007	0.010
	(1.45)	(-1.40)	(-0.95)	(1.58)	(1.22)	(0.95)	(0.64)	**(2.55)**	(-0.93)	(0.67)
β	**0.799*** **	**0.935*** **	**0.732*** **	**0.925*** **	**0.968*** **	**-0.861*** **	**0.972*** **	**0.627*** **	**0.992*** **	**0.967*** **
	(5.55)	**(17.54)**	**(2.73)**	**21.377**	**(30.34)**	**(-2.95)**	**(24.38)**	**(4.91)**	**(112.34)**	**(16.84)**
DCCX(1,1)										
ρ	**0.163** **	0.045	**0.086*** **	**0.142*** **	0.043	**-0.305*** **	0.045	-0.041	0.041	**0.146*** **
	(2.88)	(1.25)	**(11.96)**	**(3.19)**	(0.48)	**(-7.91)**	(0.88)	(-0.75)	(1.26)	**(3.84)**
α	0.045	-0.020	**-0.040*** **	0.026	0.036	0.045	0.008	**0.088** **	**-0.062*** **	**-0.058** **
	(1.31)	(-1.06)	**(-4.35)**	(1.09)	(1.05)	(0.82)	(0.24)	**(2.26)**	**(-5.72)**	**(-2.08)**
β	**0.818*** **	**0.928*** **	**0.996*** **	**0.727*** **	**0.936*** **	-0.197	**0.768*** **	**0.629*** **	**0.590*** **	0.529
	(5.33)	**(23.31)**	**(88.70)**	**(7.11)**	**(13.09)**	(-0.62)	**(2.13)**	**(3.52)**	**(31.34)**	(1.60)
ϕ_1	-0.030	-0.003	0.007	**-0.042* **	-0.022	0.177	-0.036	0.095	0.164	0.118
	(-0.48)	(-0.11)	(1.23)	**(-1.71)**	(-1.14)	(0.72)	(-1.09)	(0.50)	(1.30)	(0.74)
ϕ_2	-0.003	-0.012	0.009	**-0.075*** **	**-0.066* **	-0.199	0.411	-0.081	**-0.109*** **	0.244
	(-0.04)	(-0.56)	(0.97)	**(-3.05)**	**(-1.67)**	(-0.81)	(0.51)	(-1.10)	**(-8.62)**	(1.09)
ϕ_3	0.265	**0.410* **	**-0.295*** **	**-0.695*** **	0.224	**-0.381** **	-0.065	**-0.380** **	**1.422** **	**-0.746*** **
	(0.67)	**(1.65)**	**(-3.96)**	**(-4.99)**	(0.86)	**(-1.97)**	(-0.33)	**(-1.72)**	**(1.91)**	**(-3.03)**

	Euro area			**Non-Euro area**					**North America**
DCC(1,1)	NEL	POR	SPA	DEN	NOR	SWE	SWI	UK	CAN
ρ	0.046	0.042	0.017	**-0.085** **	-0.028	**-0.102** **	**-0.099** **	0.086	**0.204*** **
	(0.88)	(1.47)	(0.51)	**(-2.39)**	(-0.91)	**(-2.05)**	**(-2.00)**	(0.71)	**(4.02)**
α	0.019	-0.012	**-0.027*** **	-0.021	**-0.052*** **	0.019	**0.057* **	0.005	0.051
	(1.19)	(-1.27)	**(-44.43)**	(-1.54)	**(-4.13)**	(0.87)	**(1.86)**	(0.91)	(1.53)
β	**0.909*** **	**0.978*** **	**0.826*** **	**0.831*** **	**0.784*** **	**0.881*** **	**0.669*** **	**0.991*** **	**0.795*** **
	(11.70)	**(44.33)**	**(6.77)**	**(5.51)**	**(7.57)**	**(7.26)**	**(3.80)**	**(99.27)**	**(6.67)**
DCCX(1,1)									
ρ	0.023	0.059	0.011	**-0.101*** **	-0.027	**-0.080** **	-0.094	0.100	**0.203*** **
	(0.53)	(1.57)	(0.26)	**(-2.92)**	(-0.89)	**(-1.98)**	(-1.57)	(1.48)	**(3.88)**
α	-0.009	-0.018	-0.003	**-0.072*** **	-0.017	-0.002	**0.064** **	**0.021** **	**0.062* **
	(-0.47)	(-1.12)	(-0.07)	**(-2.70)**	(-1.13)	(-0.06)	**(2.10)**	**(1.96)**	**(1.71)**
β	**0.954*** **	**0.896*** **	**0.639** **	**0.687*** **	**0.864*** **	**0.561*** **	**0.778*** **	**0.951*** **	**0.750*** **
	(21.70)	**(11.77)**	**(3.24)**	**(4.41)**	**(17.74)**	**(3.79)**	**(9.30)**	**(51.42)**	**(3.53)**
ϕ_2	0.062	0.031	-0.007	0.055	**-0.019** **	0.048	0.006	**-0.041** **	0.006
	(1.40)	(0.20)	(-0.10)	(1.01)	**(-2.38)**	(1.18)	(0.09)	**(-2.29)**	(0.07)
ϕ_2	-0.028	**-0.025* **	-0.086	-0.005	**-0.036*** **	**-0.070* **	-0.066	-0.004	-0.040
	(-1.16)	**(-1.65)**	(-0.95)	(-0.20)	**(-2.95)**	**(-1.76)**	(-1.12)	(-0.23)	(-0.40)
ϕ_3	**-0.600*** **	-0.097	0.286	0.608	**-0.133* **	0.049	**0.962* **	**-0.207** **	0.474
	(-2.96)	(-0.21)	(0.93)	(1.40)	**(-1.69)**	(0.16)	**(1.77)**	**(-2.04)**	(0.66)

Table C.7: Correlation decomposition. The table illustrates whether a country experienced contagion (C) or flight-to-quality (F). The magnitude of excessive correlation movements, measured in terms of the unconditional correlation coefficient, is given in parentheses. Panel A shows the results of the Subprime Crisis and Panel B those of the Euro Crisis. We further distinguish the Subprime Crisis into a Pre-Lehman and a Post-Lehman era and the Euro Crisis into a Pre-IMF and Post-IMF bailout era. In addition to the overall correlation (left), we also report results based on the US component alone (middle) as well as the US and global component. A summary of the number of identified contagion and flight-to-quality together with their average impact is finally presented on the bottom of each panel. Please note that to be considered as contagion or flight-to-quality, the respective time-varying correlations need to display significant regime-shifts at least at the 10% significance level, after eliminating serial correlation. Standard errors are heteroskedasticity-robust (Newey and West, 1987). For details on the underlying regressions results please refer to the appendix.

Panel A: Subprime Crisis

	Overall						**US**						**US + Global**					
Asia/Pacific	Pre-Lehman		Post-Lehman		Aggregate		Pre-Lehman		Post-Lehman		Aggregate		Pre-Lehman		Post-Lehman		Aggregate	
AUS	—	—	C	(17.4%)	C	(5.9%)	—	—	C	(14.9%)	—	—	—	—	C	(14.7%)	C	(10.5%)
HKG	F	(-23.0%)	C	(25.9%)	—	—	F	(-16.9%)	C	(22.2%)	—	—	—	—	C	(22.9%)	—	—
JAP	—	—	C	(13.9%)	—	—	—	—	C	(21.4%)	—	—	C	(16.4%)	C	(16.8%)	C	(24.6%)
Euro area																		
AUT	—	—	C	(14.4%)	C	(5.6%)	—	—	C	(20.6%)	—	—	C	(11.5%)	C	(18.6%)	C	(16.4%)
BEL	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
FIN	—	—	C	(38.7%)	—	—	—	—	C	(34.3%)	C	(14.8%)	—	—	C	(29.0%)	C	(17.3%)
FRA	—	—	—	—	—	—	F	(-13.0%)	—	—	F	(-10.5%)	F	(-2.9%)	—	—	—	—
GER	—	—	C	(9.3%)	C	(8.0%)	—	—	—	—	—	—	—	—	C	(6.9%)	C	(5.6%)
GRE	—	—	—	—	—	—	—	—	C	(18.6%)	—	—	—	—	C	(13.3%)	C	(8.7%)
ITA	—	—	C	(7.2%)	—	—	F	(-14.2%)	—	—	—	—	F	(-4.3%)	C	(5.9%)	—	—
NEL	F	(-18.4%)	—	—	F	(-16.9%)	F	(-18.0%)	—	—	F	(-16.1%)	F	(-9.7%)	—	—	F	(-8.4%)
POR	—	—	C	(21.9%)	C	(9.0%)	—	—	C	(20.8%)	—	—	—	—	C	(21.6%)	C	(14.3%)
SPA	—	—	C	(9.1%)	—	—	—	—	—	—	—	—	—	—	C	(6.9%)	—	—
Non-Euro																		
DEN	—	—	C	(13.6%)	—	—	—	—	—	—	—	—	—	—	C	(11.1%)	C	(6.9%)
NOR	—	—	C	(23.3%)	C	(8.8%)	—	—	C	(17.3%)	—	—	—	—	C	(19.0%)	C	(15.6%)
SWE	F	(-8.8%)	—	—	—	—	—	—	C	(14.1%)	—	—	—	—	C	(10.7%)	—	—
SWI	—	—	C	(8.0%)	C	(7.7%)	—	—	—	—	—	—	—	—	C	(4.3%)	—	—
UK	F	(-6.4%)	—	—	—	—	—	—	C	(10.3%)	—	—	—	—	C	(5.1%)	—	—
North America																		
CAN	F	(-7.3%)	C	(8.7%)	—	—	—	—	C	(11.8%)	—	—	—	—	C	(9.2%)	—	—
Total																		
Contagion	0	—	13	(16.3%)	6	(7.5%)	0	—	11	(18.8%)	1	(14.8%)	2	(13.9%)	16	(13.5%)	9	(13.3%)
Flight-to-quality	5	(-12.8%)	0	—	1	(-16.9%)	4	(-15.5%)	0	—	2	(-13.3%)	3	(-5.6%)	0	—	1	(-8.4%)

Table C.7 continued

Panel B: Euro Crisis																		
	Overall						**US**						**US + Global**					
Asia/Pacific	Pre-IMF		Post-IMF		Aggregate		Pre-IMF		Post-IMF		Aggregate		Pre-IMF		Post-IMF		Aggregate	
AUS	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
HKG	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
JAP	—	—	—	—	—	—	—	—	C	(27.3%)	C	(21.3%)	—	—	—	—	—	—
Euro area																		
AUT	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
BEL	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
FIN	C	(16.6%)	C	(24.0%)	C	(18.0%)	C	(19.8%)	C	(26.2%)	C	(23.0%)	C	(14.5%)	C	(20.3%)	C	(16.7%)
FRA	F	(-7.2%)	F	(-12.0%)	F	(-9.2%)	—	—	F	(-9.7%)	F	(-7.4%)	F	(-8.1%)	F	(-13.1%)	F	(-10.1%)
GER	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
GRE	F	(-33.1%)	F	(-44.9%)	F	(-35.6%)	F	(-31.9%)	F	(-46.3%)	F	(-36.4%)	F	(-31.6%)	F	(-46.7%)	F	(-25.3%)
ITA	F	(-19.8%)	F	(-37.1%)	F	(-21.7%)	F	(-14.9%)	F	(-27.6%)	F	(-19.6%)	F	(-19.3%)	F	(-34.2%)	F	(-18.5%)
NEL	—	—	—	—	—	—	—	—	—	—	—	—	F	(-6.0%)	F	(-6.3%)	F	(-6.5%)
POR	F	(-23.0%)	F	(-40.4%)	F	(-27.4%)	F	(-22.3%)	F	(-37.5%)	F	(-27.0%)	F	(-23.6%)	F	(-40.1%)	F	(-25.2%)
SPA	F	(-13.4%)	F	(-25.1%)	F	(-17.2%)	F	(-11.9%)	F	(-19.9%)	F	(-15.2%)	F	(-15.3%)	F	(-25.8%)	F	(-18.3%)
Non-Euro area																		
DEN	—	—	F	(-13.2%)	F	(-9.7%)	—	—	F	(-13.0%)	F	(-10.2%)	F	(-11.3%)	F	(-16.9%)	F	(-13.3%)
NOR	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
SWE	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
SWI	—	—	—	—	—	—	—	—	—	—	—	—	F	(-4.6%)	F	(-5.6%)	F	(-4.7%)
UK	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
North America																		
CAN	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
Total																		
Contagion	1	(16.6%)	1	(24.0%)	1	(18.0%)	1	(19.8%)	2	(26.8%)	2	(22.2%)	1	(14.5%)	1	(20.3%)	1	(16.7%)
Flight-to-quality	5	(-19.3%)	6	(-28.8%)	6	(-20.1%)	4	(-20.3%)	6	(-25.7%)	6	(-19.3%)	8	(-15.0%)	8	(-23.6%)	8	(-15.2%)

Table C.8: Correlation decomposition regressions. The table shows country-specific regressions of financial sector co-movement to identify crisis-related excessive correlation movements after controlling for first-order serial correlation. Regime shifts are allowed to differ over the course of the Subprime Crisis and Euro Crisis,

$$\rho_{0it} = \upsilon_{i0} + \upsilon_{i1}\rho_{0it-1} + \upsilon_{i2}CR_1^{Pre} + \upsilon_{i3}CR_1^{Post} + \upsilon_{i4}CR_2^{Pre} + \upsilon_{i5}CR_2^{Post} + z_{it}, \qquad i \neq 0.$$

Note that during the Subprime Crisis there are two regime shifts covering the period prior and after the demise of Lehman Brothers (CR_1^{Pre} and CR_1^{Post}). During the Euro Crisis there are another two regime shifts covering the period prior and after the last IMF-led sovereign bailout occured (CR_2^{Pre} and CR_2^{Post}). t-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust (Newey and West, 1987). LB denotes the p-value of a Ljung-Box test on one period-lagged serial correlation in the residuals. *** (**, *) indicates statistical significance at the 1% (5%, 10%) level.

	Asia/Pacific			Euro area						
Overall correlations	AUS	HKG	JAP	AUT	BEL	FIN	FRA	GER	GRE	ITA
Constant	0.601***	0.483***	0.324***	0.624***	0.699***	0.462***	0.835***	0.674***	0.475***	0.702***
	(34.13)	(24.18)	(10.45)	(66.82)	(70.98)	(24.21)	(139.16)	(49.87)	(25.40)	(44.94)
Pre-Lehman	-0.016	-0.111***	0.002	0.027	-0.043	-0.042	-0.027	0.022	-0.029	-0.047
	(-0.66)	(-4.75)	(0.24)	(1.40)	(-1.34)	(-1.01)	(-1.38)	(0.59)	(-1.45)	(-1.57)
Post-Lehman	0.104***	0.125***	0.045***	0.090**	0.004	0.179***	0.009	0.063***	0.075	0.051**
	(5.50)	(2.73)	(4.78)	(2.52)	(0.16)	(6.70)	(0.59)	(4.77)	(1.52)	(2.16)
Pre-IMF	-0.013	0.036	0.010	-0.021	0.004	0.077	-0.060***	0.041	-0.157***	-0.139**
	(-0.48)	(0.97)	(0.29)	(-0.75)	(0.12)	(1.66)	(-2.83)	(1.55)	(-2.98)	(-2.44)
Post-IMF	-0.015	0.029	0.022	-0.054	-0.009	0.111**	-0.100***	0.016	-0.213***	-0.260***
	(-0.34)	(0.58)	(0.46)	(-1.62)	(-0.31)	(2.39)	(-4.09)	(0.57)	(-4.78)	(-4.38)
AR(1)	0.865***	0.840***	0.941***	0.792***	0.774***	0.823***	0.817***	0.798***	0.867***	0.874***
	(39.98)	(31.87)	(84.88)	(22.44)	(19.70)	(30.30)	(31.74)	(34.08)	(33.57)	(32.29)
LB(1)	0.408	0.278	0.152	0.267	0.025	0.020	0.539	0.546	0.220	0.268
Adj. R-squared	0.775	0.744	0.896	0.671	0.610	0.761	0.776	0.661	0.872	0.885
US component										
Constant	0.530***	0.483***	0.254***	0.505***	0.614***	0.450***	0.680***	0.631***	0.427***	0.626***
	(33.02)	(30.53)	(19.19)	(37.13)	(47.37)	(26.71)	(51.29)	(50.95)	(24.30)	(38.93)
Pre-Lehman	-0.057	-0.082*	-0.013	0.000	-0.085	-0.018	-0.108*	-0.070	-0.044	-0.100*
	(-0.87)	(-1.81)	(-0.34)	(0.00)	(-1.33)	(-0.27)	(-1.87)	(-1.03)	(-0.84)	(-1.79)
Post-Lehman	0.090**	0.107**	0.069***	0.129***	0.051	0.159***	0.039	0.055	0.088**	0.068
	(2.36)	(2.42)	(2.75)	(3.52)	(1.20)	(8.54)	(0.74)	(1.24)	(2.11)	(1.42)
Pre-IMF	0.012	0.022	0.058	0.007	-0.010	0.091*	-0.043	0.010	-0.152***	-0.105**
	(0.36)	(0.64)	(1.45)	(0.19)	(-0.29)	(1.86)	(-1.63)	(0.33)	(-2.72)	(-2.47)
Post-IMF	0.024	0.013	0.089**	-0.011	-0.035	0.121***	-0.081**	-0.013	-0.220***	-0.194***
	(0.56)	(0.27)	(1.99)	(-0.29)	(-0.98)	(2.79)	(-2.50)	(-0.41)	(-5.11)	(-4.44)
AR(1)	0.850***	0.834***	0.851***	0.834***	0.839***	0.825***	0.851***	0.826***	0.869***	0.868***
	(37.71)	(33.88)	(36.93)	(33.72)	(35.45)	(28.39)	(35.11)	(32.93)	(35.27)	(42.28)
LB(1)	0.363	0.837	0.211	0.706	0.666	0.821	0.636	0.355	0.329	0.578
Adj. R-squared	0.730	0.709	0.779	0.678	0.709	0.753	0.756	0.686	0.864	0.829
US + global component										
Constant	0.643***	0.562***	0.378***	0.633***	0.729***	0.566***	0.815***	0.744***	0.531***	0.759***
	(50.06)	(36.45)	(19.42)	(66.82)	(91.96)	(37.82)	(154.53)	(92.01)	(22.80)	(59.94)
Pre-Lehman	0.016	-0.032	0.053***	0.072***	-0.030	0.015	-0.024*	0.015	0.013	-0.030**
	(0.49)	(-1.47)	(3.68)	(3.83)	(-1.15)	(0.45)	(-1.85)	(0.62)	(0.61)	(-2.03)
Post-Lehman	0.088***	0.111***	0.054***	0.116***	0.013	0.134***	0.009	0.047***	0.063***	0.041***
	(11.33)	(5.00)	(5.35)	(9.99)	(0.72)	(7.05)	(0.61)	(5.45)	(3.93)	(2.94)
Pre-IMF	-0.015	0.004	0.009	-0.020	-0.014	0.067	-0.068***	0.006	-0.150*	-0.136**
	(-0.62)	(0.15)	(0.30)	(-0.82)	(-0.56)	(1.79)	(-3.45)	(0.30)	(-1.93)	(-2.46)
Post-IMF	-0.008	-0.010	0.024	-0.044	-0.035	0.094***	-0.110***	-0.018	-0.222***	-0.240***
	(-0.23)	(-0.23)	(0.57)	(-1.51)	(-1.38)	(2.73)	(-5.50)	(-0.84)	(-3.22)	(-4.86)
AR(1)	0.853***	0.849***	0.925***	0.813***	0.800***	0.829***	0.788***	0.784***	0.914***	0.872***
	(35.66)	(35.33)	(64.65)	(31.02)	(24.72)	(31.37)	(26.91)	(30.32)	(41.90)	(34.57)
LB(1)	0.569	0.370	0.905	0.298	0.043	0.217	0.372	0.759	0.215	0.497
Adj. R-squared	0.754	0.746	0.883	0.750	0.651	0.779	0.779	0.632	0.937	0.912

Table C.8 continued

	Euro area			Non-Euro area					North America
Overall correlations	NEL	POR	SPA	DEN	NOR	SWE	SWI	UK	CAN
Constant	**0.727*** **	**0.465*** **	**0.635*** **	**0.546*** **	**0.543*** **	**0.656*** **	**0.756*** **	**0.769*** **	**0.737*** **
	(78.09)	**(31.92)**	**(36.54)**	**(37.95)**	**(29.74)**	**(40.67)**	**(76.96)**	**(99.70)**	**(42.59)**
Pre-Lehman	**-0.134*** **	0.016	-0.014	0.016	0.010	**-0.058*** **	0.035	**-0.049* **	**-0.054* **
	(-4.37)	(0.58)	(-0.37)	(0.62)	(0.28)	**(-2.91)**	(1.25)	**(-1.71)**	**(-1.75)**
Post-Lehman	-0.019	**0.102*** **	**0.058*** **	**0.074** **	**0.126*** **	0.065	**0.061*** **	0.040	**0.064* **
	(-0.47)	**(4.62)**	**(2.94)**	**(2.18)**	**(3.84)**	(1.11)	**(5.15)**	(1.34)	**(1.82)**
Pre-IMF	-0.035	**-0.107** **	**-0.085** **	-0.038	0.007	0.013	-0.018	-0.019	0.020
	(-1.23)	**(-2.32)**	**(-2.23)**	(-1.13)	(0.18)	(0.36)	(-0.89)	(-0.85)	(0.61)
Post-IMF	-0.033	**-0.188*** **	**-0.159*** **	**-0.072* **	0.005	0.031	-0.015	-0.010	0.018
	(-0.98)	**(-4.26)**	**(-3.15)**	**(-1.86)**	(0.10)	(0.85)	(-0.56)	(-0.43)	(0.48)
AR(1)	**0.808*** **	**0.843*** **	**0.878*** **	**0.832*** **	**0.863*** **	**0.833*** **	**0.819*** **	**0.810*** **	**0.885*** **
	(28.45)	**(38.11)**	**(47.31)**	**(30.31)**	**(31.48)**	**(29.97)**	**(36.60)**	**(30.64)**	**(34.65)**
LB(1)	0.361	0.297	0.415	0.601	0.088	0.434	0.349	0.731	0.136
Adj. R-squared	0.743	0.840	0.817	0.720	0.750	0.720	0.703	0.676	0.806
US component									
Constant	**0.634*** **	**0.385*** **	**0.599*** **	**0.505*** **	**0.501*** **	**0.598*** **	**0.648*** **	**0.661*** **	**0.643*** **
	(40.15)	**(30.57)**	**(41.31)**	**(32.82)**	**(26.55)**	**(38.06)**	**(50.86)**	**(43.34)**	**(34.75)**
Pre-Lehman	**-0.131*** **	-0.036	-0.085	-0.062	-0.044	-0.080	-0.083	-0.079	-0.086
	(-2.77)	(-0.69)	(-1.42)	(-1.23)	(-0.71)	(-1.39)	(-1.27)	(-1.20)	(-1.32)
Post-Lehman	0.036	**0.097*** **	0.065	0.057	**0.094** **	**0.093* **	0.059	**0.079* **	**0.087* **
	(0.66)	**(3.44)**	(1.50)	(1.16)	**(2.31)**	**(1.83)**	(1.28)	**(1.67)**	**(1.79)**
Pre-IMF	-0.005	**-0.104*** **	**-0.075** **	-0.044	0.019	0.031	-0.020	0.004	0.039
	(-0.15)	**(-2.61)**	**(-2.32)**	(-1.43)	(0.44)	(0.79)	(-0.73)	(0.11)	(0.87)
Post-IMF	-0.005	**-0.174*** **	**-0.127*** **	**-0.071* **	0.016	0.049	-0.034	0.007	0.049
	(-0.11)	**(-4.49)**	**(-3.02)**	**(-1.78)**	(0.31)	(1.26)	(-0.96)	(0.20)	(1.06)
AR(1)	**0.863*** **	**0.837*** **	**0.857*** **	**0.851*** **	**0.871*** **	**0.842*** **	**0.845*** **	**0.865*** **	**0.876*** **
	(42.52)	**(32.90)**	**(43.50)**	**(38.32)**	**(39.41)**	**(38.73)**	**(36.79)**	**(38.99)**	**(43.81)**
LB(1)	0.319	0.626	0.577	0.288	0.556	0.628	0.636	0.525	0.440
Adj. R-squared	0.777	0.808	0.776	0.733	0.755	0.727	0.717	0.743	0.790
US + global component									
Constant	**0.776*** **	**0.493*** **	**0.717*** **	**0.616*** **	**0.597*** **	**0.705*** **	**0.776*** **	**0.801*** **	**0.731*** **
	(98.05)	**(36.83)**	**(57.98)**	**(53.01)**	**(37.54)**	**(57.62)**	**(115.55)**	**(103.45)**	**(48.78)**
Pre-Lehman	**-0.070*** **	0.026	-0.003	0.024	0.043	-0.022	-0.006	-0.015	-0.011
	(-3.97)	(1.38)	(-0.16)	(1.62)	(1.28)	(-1.49)	(-0.32)	(-0.76)	(-0.33)
Post-Lehman	0.007	**0.100*** **	**0.043*** **	**0.061** **	**0.103*** **	**0.070** **	**0.033*** **	**0.039** **	**0.068*** **
	(0.28)	**(10.88)**	**(5.55)**	**(3.46)**	**(11.92)**	**(2.37)**	**(3.78)**	**(2.03)**	**(4.31)**
Pre-IMF	**-0.044* **	**-0.110** **	**-0.097** **	**-0.062** **	0.001	0.010	**-0.035* **	-0.024	0.015
	(-1.90)	**(-2.42)**	**(-2.39)**	**(-2.33)**	(0.04)	(0.34)	**(-1.88)**	(-1.26)	(0.47)
Post-IMF	**-0.045* **	**-0.187*** **	**-0.164*** **	**-0.092*** **	-0.006	0.026	**-0.042** **	-0.018	0.019
	(-1.65)	**(-3.98)**	**(-4.03)**	**(-2.80)**	(-0.14)	(0.93)	**(-2.04)**	(-0.95)	(0.51)
AR(1)	**0.844*** **	**0.862*** **	**0.877*** **	**0.843*** **	**0.873*** **	**0.835*** **	**0.803*** **	**0.836*** **	**0.881*** **
	(32.93)	**(42.36)**	**(44.50)**	**(32.45)**	**(33.85)**	**(30.48)**	**(32.34)**	**(28.30)**	**(41.47)**
LB(1)	0.557	0.310	0.622	0.517	0.499	0.572	0.427	0.462	0.326
Adj. R-squared	0.765	0.884	0.857	0.776	0.775	0.725	0.685	0.703	0.788

Marginal Effect of Exogenous Variable

In DCC-type models the marginal effect of an exogenous variable on residual correlations is ambiguous as Li (2011) argues. The reason is that the exogenous variable affects the residual covariance and variance processes differently, thereby allowing changes in the covariance being overcompensated by those in the variance.

For an analytical examination recall the definition of the residual correlation coefficient,

$$\rho^R_{12t} = \frac{q_{12t}}{\sqrt{q_{11t}q_{22t}}} = \frac{C_{12t} + \phi_3 X_{t-1}}{\sqrt{(C_{11t} + \phi_3 X_{t-1})(C_{22t} + \phi_3 X_{t-1})}} \tag{C.1}$$

where

$$\begin{aligned}
C_{11t} &= (1-\alpha-\beta) + (\alpha + \phi_1 XTRM_{1t-1} + \phi_2 XTRM_{2t-1})\xi^2_{1t-1} + \beta q_{11t-1} \\
C_{12t} &= \rho_{12}(1-\alpha-\beta) + (\alpha + \phi_1 XTRM_{1t-1} + \phi_2 XTRM_{2t-1})\xi_{1t-1}\xi_{2t-1} + \beta q_{12t-1}, \\
C_{22t} &= (1-\alpha-\beta) + (\alpha + \phi_1 XTRM_{1t-1} + \phi_2 XTRM_{2t-1})\xi^2_{2t-1} + \beta q_{22t-1}.
\end{aligned}$$

The partial derivation of the correlation coefficient with respect to the exogenous variable is $\frac{\partial \rho^{Res} o_{12t}}{\partial X_{t-1}} = \frac{\phi_3}{\sqrt{q_{11t}q_{22t}}}\left(1 - \frac{q_{12t}(q_{11t}+q_{22t})}{2q_{11t}q_{22t}}\right)$. Hence depending on the signs of ϕ_3 and q_{12t} as well as the size of $(q_{11t} + q_{22t})/(2q_{11t}q_{22t})$, the marginal effect of X_{t-1} is either positive or negative. If $q_{12t} = 0$, the second term in equation (10) is positive since q_{11t} and q_{22t} are both non-negative. Given these circumstances, an increase (decrease) in the global risk factor provokes a rise (decline) in the residual correlation. If $q_{12t} > 0$, the same result follows as long as $(q_{11t} + q_{22t})/(2q_{11t}q_{22t}) < 1/q_{12}$ is satisfied. Once the latter condition is violated, the effect reverses. This is the case, when an increase in X_{t-1} has a sufficiently stronger impact on variances than on the covariance. Hence, the residual correlation may decrease, even if the estimated parameter ϕ_3 is positive.

Li (2011) describes a less complex analytical derivation. However, his remarks rely on the simplifying assumption that $(q_{11t}+q_{22t})/(q_{11t}q_{22t}) = 1$. Since q_{11t} and q_{22t} are time-varying we relax this restriction.