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Frank Hespeler, Christian Witt

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Authors: Frank Hespeler, Christian Witt
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European Securities and Markets Authority (ESMA)
Economics and Financial Stability Unit
103, Rue de Grenelle
FR–75007 Paris
financialstability@esma.europa.eu

The Systemic Dimension of Hedge Fund Illiquidity and Prime Brokerage[1]

Frank Hespeler[2], Christian Witt[3]

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Abstract

We analyse the potentially vulnerable and systemically relevant financial intermediation chain established by hedge funds and prime brokers. 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.

JEL Classifications:

Keywords: Hedge funds, prime brokers, illiquidity, financial crisis, VEC

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[2] European Securities and Markets Authority (ESMA), 103 rue de Grenelle, 75007 Paris Cedex, France

[3] University of Regensburg, Universitaetsstr. 31, 93040 Regensburg, Germany

I. Introduction

The recent global financial crisis is, among other features, characterized 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 heteroscedasticity-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.[4] In this process they frequently pledge previously acquired assets as collateral with prime brokers. In addition, in many cases they authorize 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 II), 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; Gorton 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 (von Thadden 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).

[4] 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 Mayer (2009).

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 (2009b) 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 incentivizing 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., 2010; 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 II describes our set of endogenous variables and control variables. In section III we explain the model selection procedure. Next, section IV 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 V. Section VI briefly discusses our findings in light of systemic risk, and section VII concludes.

II. 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.[5]

A. 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, 2012; Joenväärä et al., 2012). On the other hand, consolidation allows for data overlaps. To eliminate those, a

5 If not otherwise indicated all data originates from Thomson Datastream.

structured consolidation process similar to those used in Patton and Ramadorai (2012) and Joenväärä et al. (2012) is used to identify and remove duplicates.[6] Following this method, our final dataset comprises 306 hedge funds, which all belong to the so-called "billion dollar club"[7] 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 Mayer (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 (NAV) or AuM turn out to be unreliable or biased by differing leverage levels of funds (Ang et al., 2011).[8] 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.[9] The resulting residual (HFILLIQ) comprises roughly 80% of the total variation 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.[10] This variable is the first in our set of endogenous variables.

B. 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.[11] 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.[12] This last step reveals a high contribution of banking activities outside of prime brokerage for our constituents' performance (adj. R-Squared = 0.87).

Furthermore, we capture prime brokers' securities trading activities by three variables reported by the FRBNY's primary dealer database.[13] 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

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6 A more detailed description is provided in the appendix.

7 See Edelmann et al. (2012)

8 Until October 1, 2011, the popular HFR index was computed using uniform weights.

9 The asset-based strategy factors were collected from David Hsieh's website: http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls

10 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).

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

12 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.

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

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, LENDING). This first empiric evidence indicates that prime brokers generate profits by engaging in maturity transformation.[14] All three variables are normalised as of July 2001.

C. 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).[15]

D. Turmoil control variables

Periods of financial turmoil are reportedly related to unusual negative hedge fund returns (Billio et al., 2010; 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 III); 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 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.

III. 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).[16] Beyond that, HFILLIQ shows signs of non-stationarity as heteroscedasticity-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,

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

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

[16] For details on descriptive statistics of endogenous variables and their stationarity please refer to Table A.4.

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

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; for the moment excluding blip 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, heteroscedasticity, lag exclusion, normality) and structural break statistics (Chow breakpoint tests). The alternatives differ by lag length, cointegration rank and specification of the cointegration equation.

[Table A.5]

Our results displayed in Table A.5 suggest strong serial correlation in the residuals of models including one or three lags. They are therefore rejected.[17] From the remaining specifications we subsequently exclude those for which our ME and TR cointegration rank criteria are inconsistent with the estimated model specification. Only four models pass this test. Neither the average model fit[18], 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 indicates that the most robust and parsimonious model features two cointegration equations including a constant.[19] Thus, we choose this specification.

Interestingly, the test results in Table A.5 indicate no violation of the normality assumption despite significant heteroscedasticity. Indeed, a subsequent visual inspection suggests that the residuals may occasionally cluster. Hence, the model standard errors tend to underestimate the true standard deviation which. We therefore switch to heteroscedasticity-robust estimation procedures following the methodology provided in Newey and West (1987), and present below only results corrected for heteroscedasticity issues. As an additional precaution we completely ignore the 10% significance level for statistical inference.

Finally, we employ Granger causality tests[20] 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 A.8 confirm that the chosen specification is appropriate, since each of the significant parameters in the short-run equation (cf. Table A.6 below) is matched by some forecasting power of the respective pair of lagged variables.

[Table A.8]

IV. 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

17 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.

18 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.

19 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.

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

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.

A. *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 are depicted by the model's cointegration equation, which depicts the model's long-run trend. 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.[21] The resulting cointegration equations are,

$$\begin{pmatrix} PBER_t \\ HFILLIQ_t \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \end{pmatrix} \begin{pmatrix} LENDING_t \\ NETPOS_t \\ FINANCING_t \end{pmatrix}. \quad (2)$$

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.

[Table A.6]

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

[21] 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.

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.7), 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 in the first and third lag (0.262 and 0.275).[22] 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).

B. *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[23]), 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.[24] Supposedly due to growing haircuts and margin requirements (Gorton and

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

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

[24] 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. 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.

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 summarize, 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.

C. *High levels of stress in financial markets tend to weaken the intermediation chain formed by hedge funds and prime brokers, since prime brokers start to hoard liquid securities.*

According to Table A.8, 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.[25] 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 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, 2009b; 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. Fig. F.4(b)), 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

[25] 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.

their excess returns. Hedge funds, on the other hand, are able to exploit the increased demand for illiquid assets or their securitized 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.

[Figure 4]

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.

[Figures F.3A]

As depicted in Figure F3.A, 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% 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%).

[Figure F.3B]

To the contrary, the variance decomposition illustrating the risk-related shock dissemination via prime broker *lending* (see Figure F3.B), appears to be mainly driven by prime brokers' security 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 (20-30%). Instead, their variation is mainly generated by securities holdings (around 50%) and lending activity (30-20%). 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 the volumes of prime brokers' financing and lending activities. 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 summarize, 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.

D. Disruptions in the financial intermediation chain formed by hedge funds and prime brokers 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 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. Fig. F.4), 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. Fig. F.4(a) and Table A.7). 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. Hence, their demand for additional lending increases. But 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 in general 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 (Fig. F.3A, F.3B).

Similarly, the variance decompositions of a shock to the hedge fund illiquidity premium displayed in Figure F.1 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.

[Figure F.1]

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.

[Figure F.2]

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. Fig. F.2). 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 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 summarize, 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.

E. Adverse shocks to either the illiquidity premium of hedge funds, the refinancing volume of prime brokers' in repo markets or their outright holdings of securities all 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 C). 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.

V. 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 F.5A, 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 F.5B. 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 III.

Second, to evaluate the resilience of the benchmark model, we repeat the analysis of Section III 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 F.6. We start by applying a narrower set of prime brokers––ignoring those that do not account for at least 5% of all observed mandates.[26] 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. [27] All of these modifications do hardly produce any reaction in our two robustness criteria. But the 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.[28] The latter variables 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 III is stable to modifications in the model selection procedure, in the construction of

[26] 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.

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

[28] 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 is accordingly still ensured.

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.

VI. 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 brokers––i.e. fluctuations in their securities holdings––tends 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 (von Thadden 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. (2010) 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 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.

VII. Concluding Remarks

We analyse the potentially vulnerable and systemically relevant financial intermediation chain established by hedge funds and prime brokers in a heteroscedasticity-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, 2009b) 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 emphasize 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 checks––variations in the construction of endogenous variables, a modified model selection procedure, inclusion of potentially omitted variables––reconfirm that the estimated heteroscedasticity-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.

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Appendix

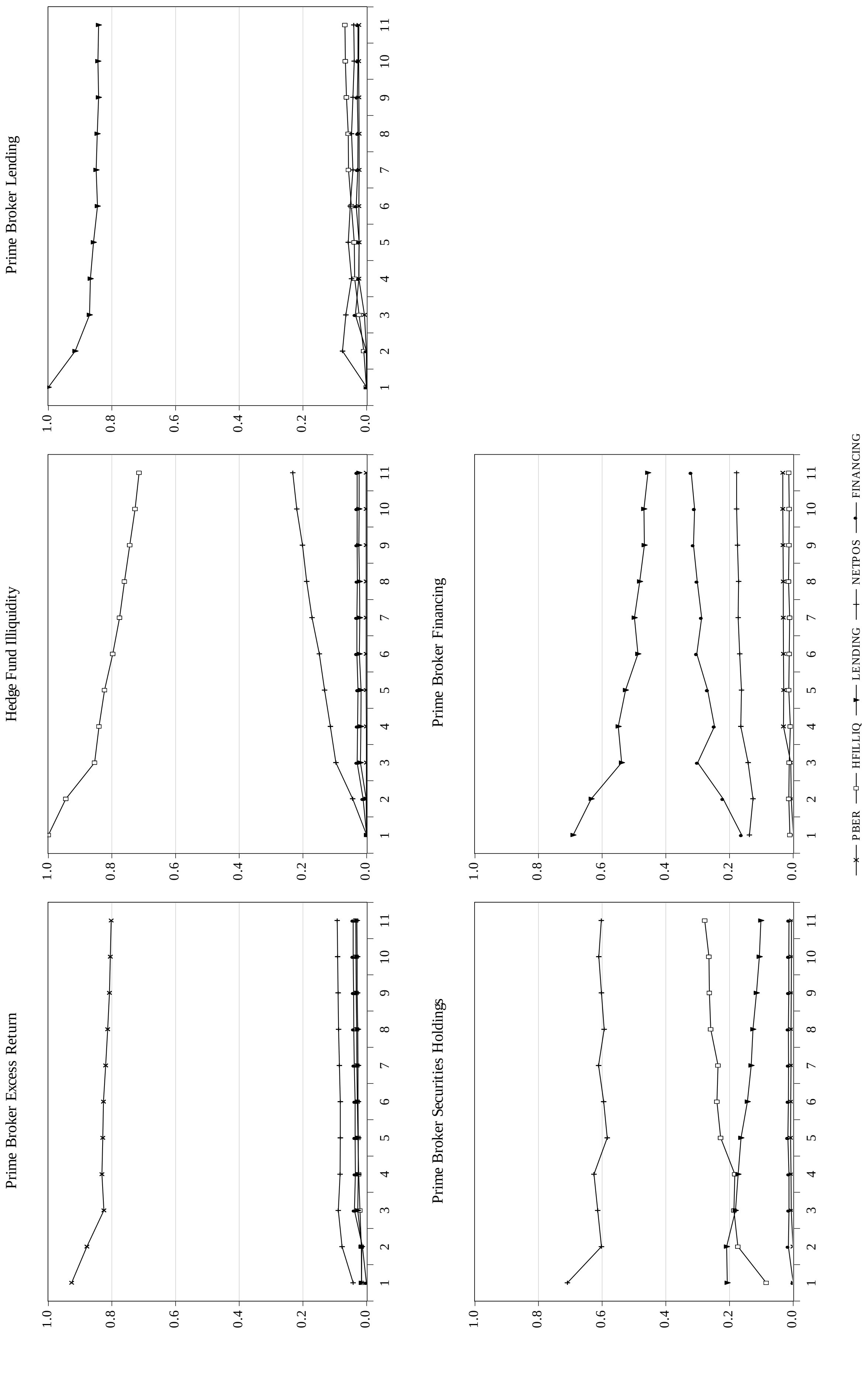

Figure F.1: Shocks to Hedge Funds. This Figure displays variance decompositions of the endogenous variables. Results are based on Luetkepohl (2005). Cholesky Order: HFILLIQ, LENDING, NETPOS, FINANCING, PBER. Vertical axes are in percentages, horizontal axes are in months.

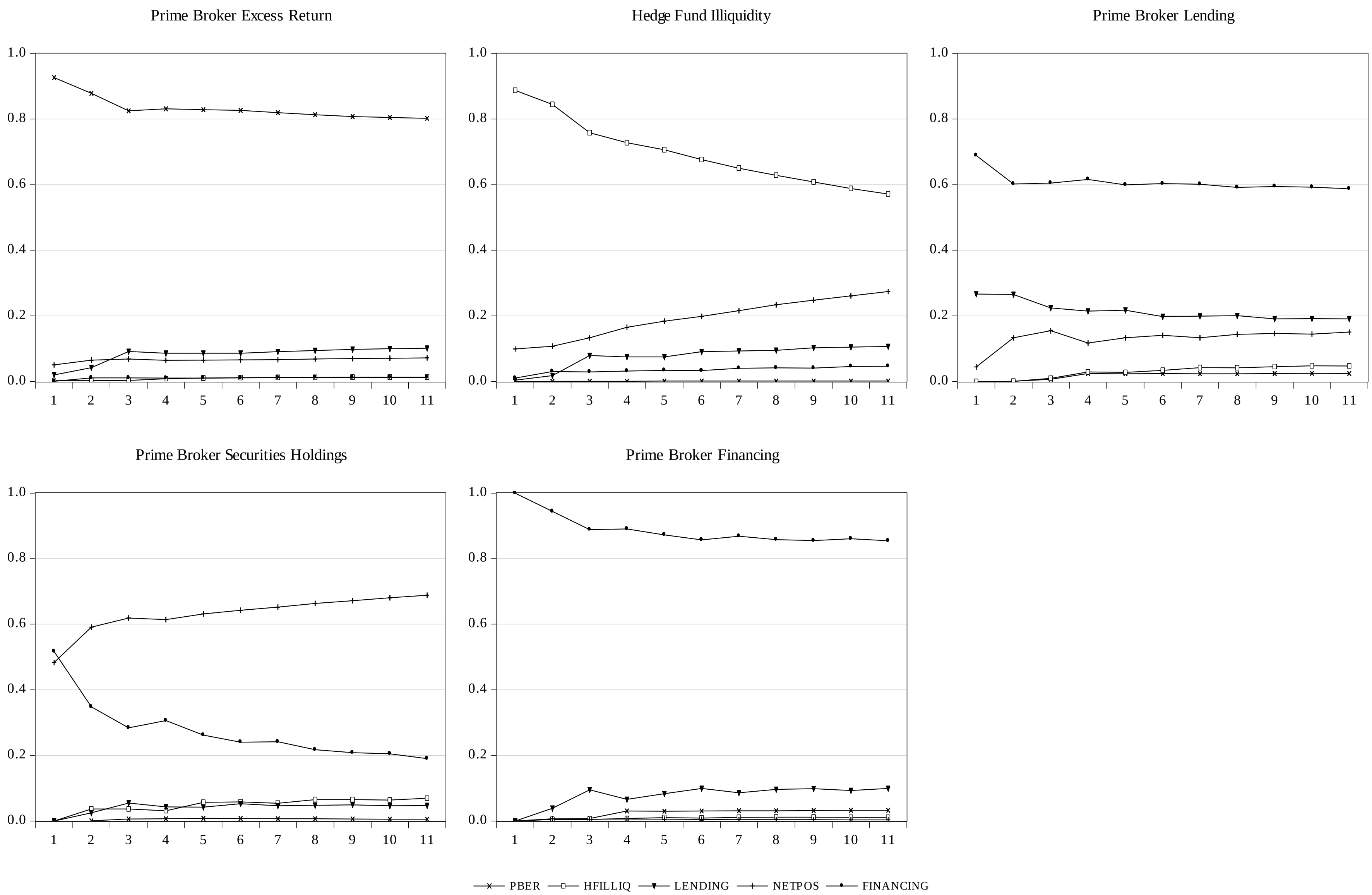

Figure F.2: Shocks to Money Markets. This Figure displays variance decompositions of the endogenous variables. Results are based on Luetkepohl (2005). Cholesky Order: FINANCING, NETPOS, LENDING, HFILLIQ, PBER. Vertical axes are in percentages, horizontal axes are in months.

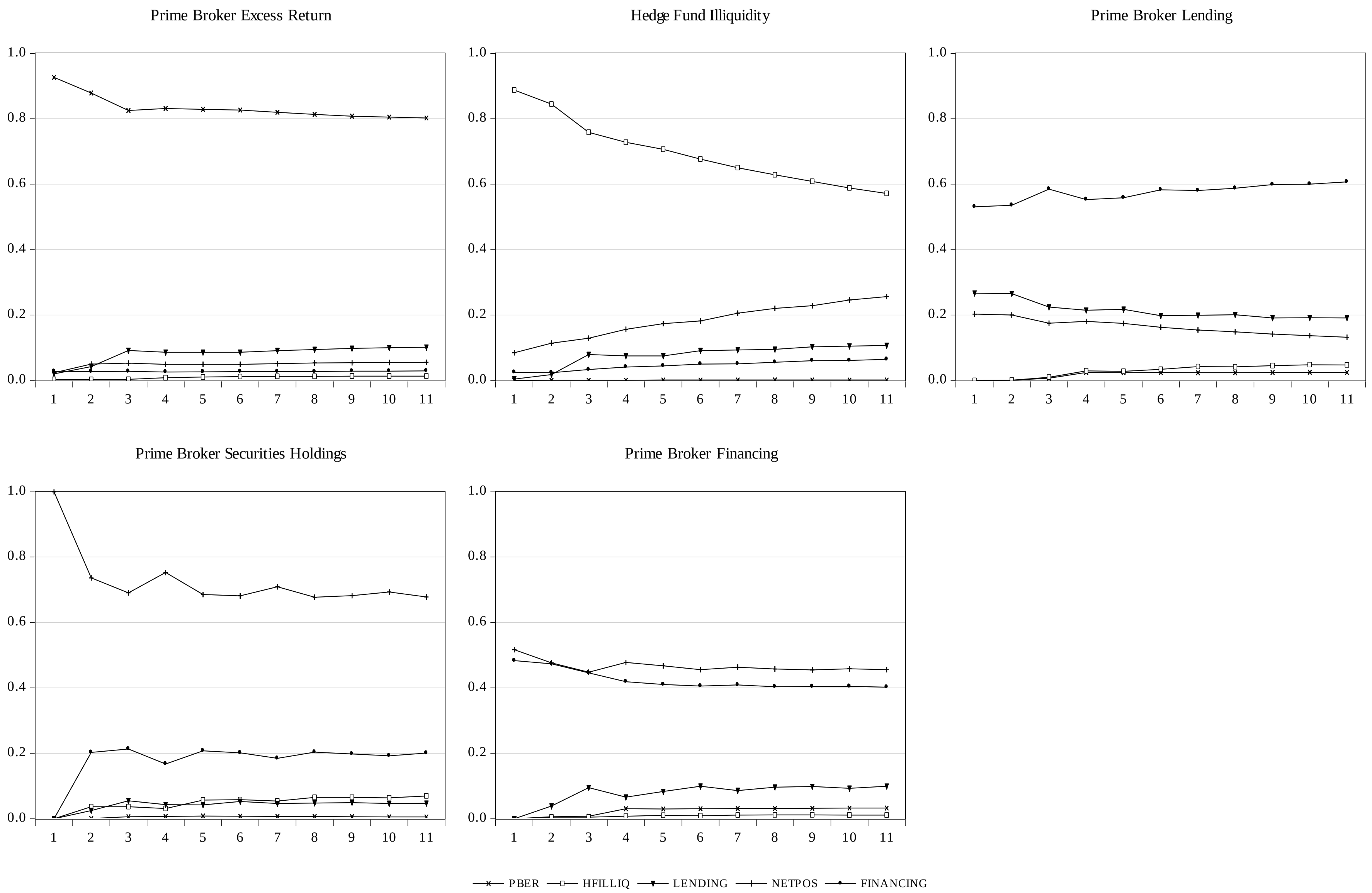

Figure F.3A: Risk Shock. This Figure displays variance decompositions of the endogenous variables. Results are based on Luetkepohl (2005). Cholesky Order: NETPOS, FINANCING, LENDING, HFILLIQ, PBER. Vertical axes are in percentages, horizontal axes are in months.

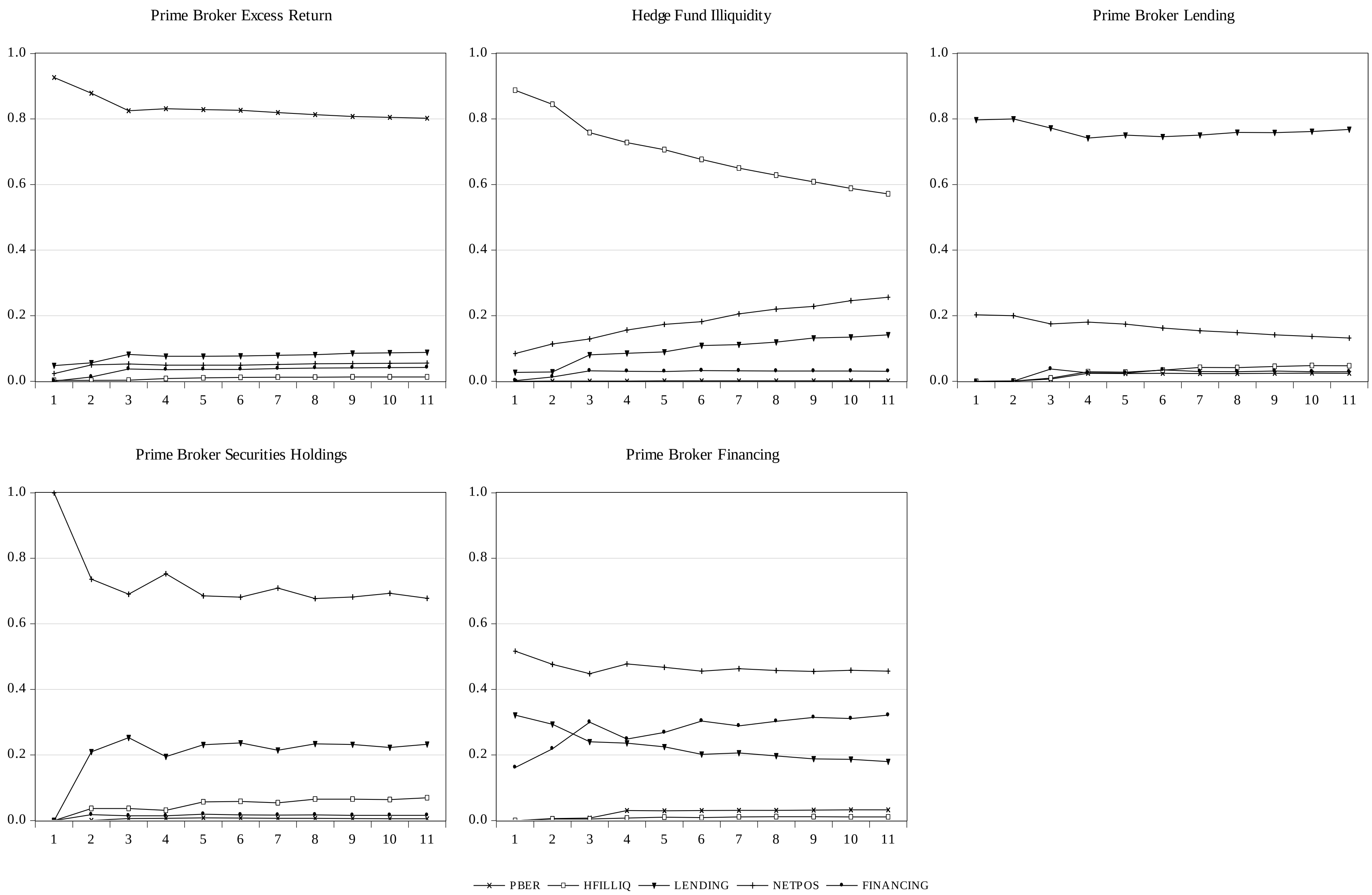

Figure F.3B: Risk Shock. This Figure displays variance decompositions of the endogenous variables. Results are based on Luetkepohl (2005). Cholesky Order: NETPOS, LENDING, FINANCING, HFILLIQ, PBER. Vertical axes are in percentages, horizontal axes are in months.

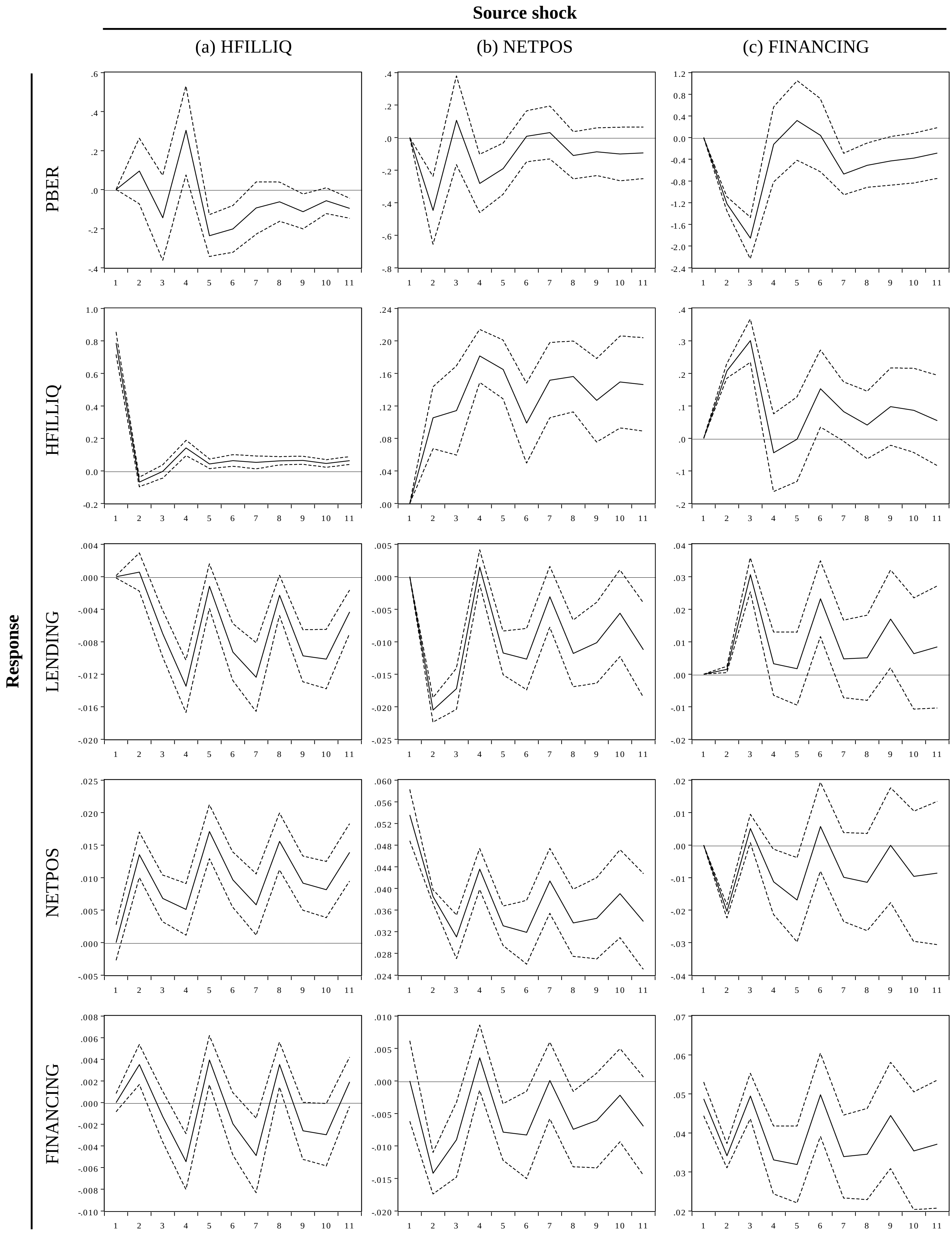

Figure F.4: Impulse Responses. This Figure displays impulse responses of the endogenous variables to shocks in (a) HFILLIQ, (b) NETPOS, (c) FINANCING. Dotted lines denote confidence levels at the 5% significance level. Vertical axes are scaled in Cholesky innovations, horizontal axes are in months.

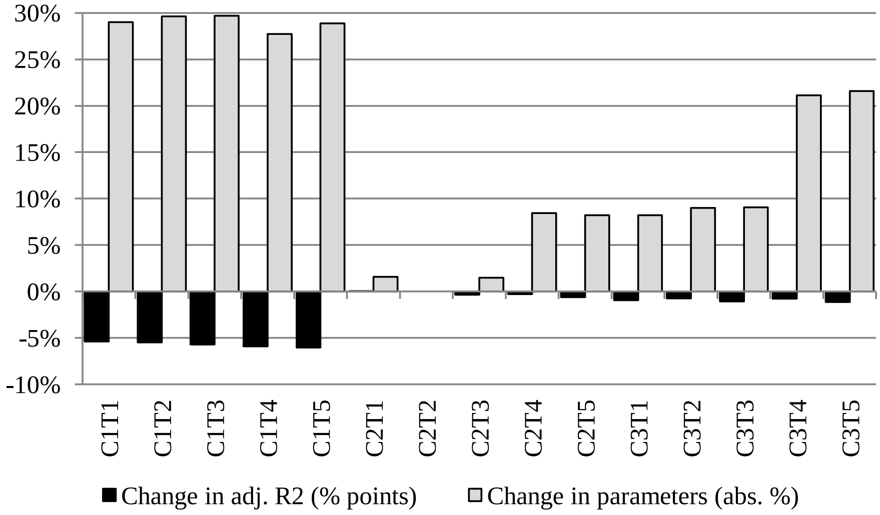

Figure F.5A: Model fit and parameter stability. This figure illustrates deviations in the overall model fit (adjusted R-Squared) and in parameter stability (absolute percentage changes) of various model specifications from the benchmark model (C2T1). Character combinations C1 to C3 represent the number 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).

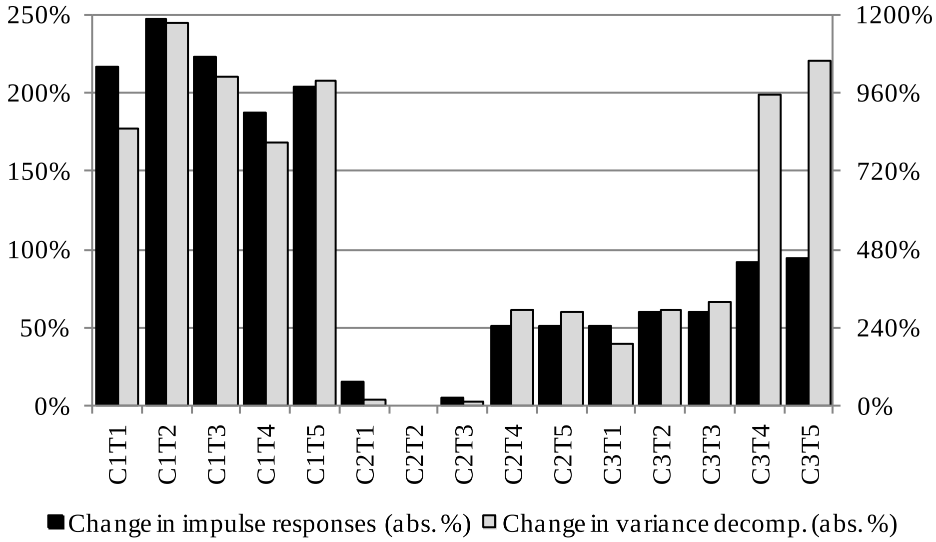

Figure F.5B: Indirect proxies of parameter stability. This figure illustrates deviations in the impulse responses and in the variance decompositions (both 3 lags) of various model specifications from the benchmark model (C2T1). Character combinations C1 to C3 represent the number of cointegration equations 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).

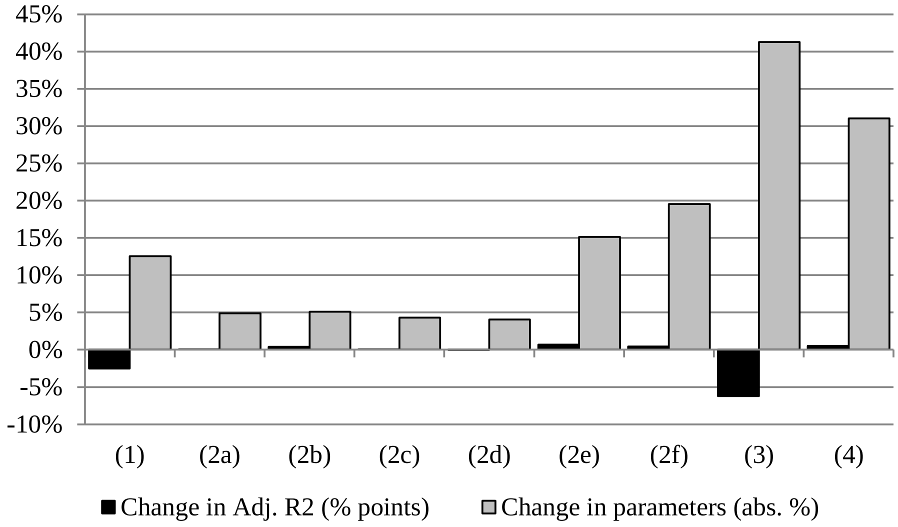

Figure F.6: Modified variable constructions and omitted variables. This figure illustrates deviations in the overall model fit (adjusted R-Squared) and in parameter stability (absolute percentage changes) of various model specifications from the benchmark model. Specifications differ in modified endogenous 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.

Table A.1: Variable definition and sources. This table contains the names of each variable, its original sources, a brief description as well as its previous use in the literature

Variable	Source	Description	Use in 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.	Agrarwal 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 and Taksler (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.	Agrarwal and Naik (2004), Boyson et al. (2010)

A.2 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 (2012) and Joenväärä 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 Joenväärä 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.

A.3 Details on prime brokers

The table below reports all prime brokers considered in the calculations. We find 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 being a joint venture of Credit Agricole and Societe Generale is replaced by its parent companies. Thus, there are finally 20 constituents.

Table A.3: Prime broker details. This table contains the names of considered prime brokers, their accumulated mandates with 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	Excluded	Uniform weight (%)	Mandates as weight (%)
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				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				5.0	NA
Man Group	Yes	1	Yes		
Merrill Lynch				5.0	NA
MF Global	Yes	1	Yes		
Morgan Stanley	Yes	22		5.0	11.0
Newedge – joint venture of:	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**	**5**	**100**	**100.0**

Please not 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 A.4: 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 Stats	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
First 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
First 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 A.5: 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 & 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, 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 Lluetkepohl (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 A.5: Selection of VEC model - continued. 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 & 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, 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 Lluetkepohl (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			Hetero-skedasticity	Normality			Lag exclusion			Robustness: # of detections		
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

Table A.6: VEC model estimates of the long-run relationship. This table contains VEC model estimates of the long-run equation including a constant: $\Delta y_t = \alpha(c' + \beta' y_{t-1}) + \sum_{i=1}^{p-1} \Phi_i^* \Delta y_{t-i} + BX_t + \varepsilon_t$, 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 RET. VOLA ACT.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. *** (**) denotes significance at the 1% (5%) level.

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

Table A.7: VEC model estimates of the short-run relationship. This table contains VEC model estimates of the short-run equation including a constant: $\Delta y_t = \alpha(c' + \beta' y_{t-1}) + \sum_{i=1}^{p-1} \Phi_i^* \Delta y_{t-i} + BX_t + \varepsilon_t$, 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 RET.VOLA ACT.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. *** (**) denotes significance at the 1% (5%) level. Standard errors are heteroscedasticity and autocorrelation robust (HAC).

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

Table A.8: 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. *** (**,*) denotes 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*****	**0.001*****

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