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Firm-specific shocks and contagion:
are banks special?

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Abstract

This paper builds a database of idiosyncratic shocks (events) in global banks and car manufacturers (as representative of non-financial firms), and focuses on how these influence a number of macroeconomic and firm-specific variables in the short- and medium-term. We find that these shocks spawn large and persistent effects on the firms' own market valuation in terms of their equity prices, CDS spreads and expected default probabilities, while contagion across firms in both sectors is generally small. Surprisingly, we find that spill-overs of bank-related events are not significantly different from the car sector, suggesting that, at least from this perspective, banks are not special. We also investigate whether our events are “granular”, i.e. influencing aggregate variables such as the VIX, equity indexes and key exchange rates, with mixed results.

Keywords: Global banks, contagion, event study, systemic risk, local projections.

JEL classification: F3, G2.

Non-technical summary

It is increasingly recognised that idiosyncratic shocks to individual large firms can have macroeconomic consequences (Gabaix, 2011) in addition to, and independent of, aggregate shocks that have been traditionally emphasized in economics. A key reason for why this is the case is that the distribution of firm size is fat tailed, although interconnectedness may also matter (Acemoglu et al., 2015). Idiosyncratic shocks provide an interesting route to identify exogenous events that drive the macro-economy by running “event studies” not only on financial, but also on macroeconomic variables. Recent papers have indeed emphasized the granular nature of large institutional investors (Ben-David et al., 2016), banks (Bremus et al., 2018), non-financial firms (Di Giovanni et al., 2014, using French data) and trade (Eaton et al., 2016).

Against this background, the contribution of our paper is twofold. First, we provide a database of idiosyncratic events affecting the expected profitability of two types of large firms, namely global banks and the world’s largest car companies. We identify a panoply of events, notably following earnings releases, mergers and acquisitions, changes in the firm top management, scandals and announcement of judicial investigations, and so forth. To identify these events, we first use a purely econometric approach to determine large idiosyncratic movements in equity returns. We are careful in controlling for common market developments at the global and national level to identify events that can be safely labelled as idiosyncratic, i.e. affecting only one individual firm at the time. We then add narrative evidence on the origins of these events to ensure to clearly isolate events which are not driven by common macroeconomic shocks but are indeed following from firm-specific news.

Apart from describing the identification scheme and providing the shock database for further investigation of their “granularity”, we also document the short-term effects of these events on the firms’ market valuation and the spill-overs of these events to the market valuation of *other* firms in the same sector. Of particular interest within this contribution is the question of whether the spill-over is significantly different for banks than for car companies, on account of the special nature of banks. Global banks play a fundamental role in international finance, especially during periods of financial crisis (Cetorelli and Goldberg, 2011). Financial interconnectedness is potentially crucial for global financial stability due to the risk that events impinging on the future viability of specific banks may create a default cascade, jeopardising the stability of the whole system. As a result, distress in one part of the system is transmitted to other parts. We

find that these shocks spawn large and persistent effects on the firms' own market valuation in terms of their equity prices, CDS spreads and expected default probabilities, while contagion across firms in both sectors is generally small. Surprisingly, we find that spill-overs of bank-related events are not significantly different from the car sector, suggesting that, at least from this perspective, banks are not special. We also investigate whether our events are "granular", i.e. influencing aggregate variables such as the VIX, equity indexes and key exchange rates, with mixed results.

1 Introduction

It is increasingly recognised that idiosyncratic shocks to individual large firms can have macroeconomic consequences (Gabaix, 2011) in addition to, and independent of, aggregate shocks that have been traditionally emphasized in economics. A key reason for why this is the case is that firm size is fat tailed, e.g. following a power law distribution, although interconnectedness may also matter (Acemoglu et al., 2015). Moreover, granular shocks also provide an interesting route to identification of exogenous events driving the macro-economy, since it is possible in principle to run “event studies” not only on financial, but also on macroeconomic variables. Recent papers have indeed emphasized the granular nature of large institutional investors (Ben-David et al., 2016), banks (Bremus et al., 2018), non-financial firms (Di Giovanni et al., 2014, using French data) and trade (Eaton et al., 2016).

Against this background, the contribution of our paper is twofold. First, we provide a database of idiosyncratic events affecting the expected profitability of two types of large firms, namely global banks and the world’s largest car companies. Apart from describing the identification scheme and documenting the effects of these events on the firms’ market valuation, we also provide the shock database which can be useful for additional investigation - for example to check if these events are indeed “granular” for global financial and macroeconomic variables. Second, we document the spill-over of these events to the market valuation of *other* firms in the same sector. Of particular interest within this contribution is the question of whether the spill-over is significantly different for banks than for car companies, on account of the special nature of banks. Observe that the two contributions are closely related; indeed one cannot be sure to identify a spill-over without a clean and uncontroversial identification of exogenous and idiosyncratic firm-level events.

We identify a panoply of events, notably following earnings releases, mergers and acquisitions, changes in the firm top management, scandals and announcement of judicial investigations, and so forth. We are careful in controlling for overall market developments and to identify events that can be safely labelled as idiosyncratic, i.e. affecting only one individual firm at the time. The scheme we apply to identify idiosyncratic events relies on a two-step procedure. First, we use a purely econometric approach to determine large idiosyncratic movements in equity returns. We begin by regressing firms’ daily equity returns on four controls, that is global equity returns of the sector, equity returns of the firm’s country of incorporation, the cross-sectional average

equity returns and the VIX, and two own lags. We then take the 7-standard deviation outliers in the standardized residuals of this regression to define two dummy variables, one for positive and one for negative events. We impose two additional restrictions. First, only one firm may have an event on any given day and second, the change in the share price has to be consistent with the sign of the event. In the second step of our shock identification scheme, we collect narrative evidence supporting a firm-related origin of the events identified in the first part. This is essential to ensure to clearly isolate events which are not driven by common macroeconomic shocks but are indeed following from firm-specific news and, hence, idiosyncratic. On the basis of the first step of our shock identification strategy, we recover 55 events for the car sector and 107 for the banking sector. We could ascribe 52 of the 55 shocks to car companies and 82 of the 107 shocks to banks to a firm-related origin. This database of 134 idiosyncratic shocks is used for our analysis of the granularity and the effects of such shocks on the firms' own market valuation and contagion across firms in the same sector.

Global banks play a fundamental role in international finance, especially during periods of financial crisis (Cetorelli and Goldberg, 2011). In particular, financial interconnectedness between global banks has become a question of great importance in the post crisis world. The policy-making community, notably the Financial Stability Board (FSB), regards financial interconnectedness in general, and vulnerability contagion in particular, as an essential element of the systemic nature of large global banks. Reflecting this view, interconnectedness has been included explicitly as one of the criteria defining a Global Systemically Important Financial Institution (G-SIFI), which attracts a capital surcharge. More generally, understanding financial interconnectedness has high priority in the agenda of academics and policy-makers and in the design of a safer and more robust financial system.

Global bank interconnectedness is potentially crucial for global financial stability due to the risk that events impinging on the future viability of specific banks may create a default cascade, jeopardising the stability of the whole system. As a result, distress in one part of the system is transmitted to other parts.

As a matter of theory, the transmission channels of an idiosyncratic shock to the expected profitability of a firm in a given sector may be complex and work through several mechanisms, outlined for simplicity in Table 1, and may in principle involve both strategic substitution and complementarity. First, a negative spill-over may arise after a shock hitting (the probability

of distress of) financial institution A, which in turn has a negative impact on institution B as a counterparty, due to large direct or indirect exposure (*counterparty channel*). Second, a shock hitting institution A may induce market participants to reassess the distress probability of institution B, as it might share certain similarities with institution A, leading to a form of *information channel*. For example, if an investment bank gets into trouble, investors may reassess the risk of all investment banks. Additionally, negative news for bank A can be also regarded as good news for bank B, if the two institutions compete in the same markets, leading to a negative form of spill-over (*competition channel*). Finally, distress can be transmitted through similar exposures to the same asset class (*fire sale channel*); if bank A is a key player in the market for, say, asset backed securities, its distress might depress asset valuations and indirectly hit the balance sheet of other intermediaries. Finally, the same intermediaries may hold stocks in different firms (*shared stock ownership*). As shown in Anton and Polk (2014) and other previous contributions, shared fund ownership promotes co-movement of equity returns, over and above other joint characteristics of the firms.¹

Observe that the structure of the financial network is only in the first of these four potential transmission channels an important determinant of financial inter-connectedness and contagion. This consideration also suggests that a financial network may be fundamentally different from a physical network, such as an electricity grid, where the strength and number of connections between the nodes are the crucial elements for the propagation of shocks within the network. In fact, standard default cascades are quite difficult to generate in interbank markets (Georg, 2013). Moreover, if cross stock ownership by funds is a driver of co-movement in asset prices and returns, then the relevant network is not necessarily the sectoral one, but rather that of the financial intermediaries holding the stocks.

We compare banks and car companies in their spill-over effects because it may be assumed that the car sector is less interconnected in terms of financial exposures, in particular the counterparty channel should be much less material or even non-existent. The fire-sale channel is also likely to be limited. The information channel may be similar in the two sectors, though one may speculate that it may be more important for banks which have a more opaque balance sheet. Conversely, the competition channel is arguably stronger in the car sector, where contestability

¹Note, however, that previous analysis on shared ownership is not conditional on the source of the shock driving returns. We are not aware of analysis of the role of cross ownership *conditional on the shock being firm-specific*, which is our focus in this paper.

Channel of spill-over of an idiosyncratic shocks	Relevance for global banks and car manufacturers
Counterparty channel	Likely stronger for banks
Information channel	Likely stronger for banks, because they are more opaque
Competition channel	Likely stronger for car companies, because they are in a more contestable market
Fire sale channel	Likely more relevant for banks, because they are higher leverage and more financial assets in the balance sheet
Shared stock ownership	In principle the same for the two sectors

Table 1: Outline of the key transmission channels of an idiosyncratic shock.

is higher. Comparing banks and car companies might, therefore, tell us something about the relative importance of the theoretical transmission channels of firm-specific shocks.

Our main findings can be summarized as follows. Idiosyncratic shocks spawn large effects on the firms' own market valuation in terms of their equity prices, CDS spread and the expected default probability, while contagion across the firms in the sector is generally small. Our results do not show any prominent differences in the spill-over effects for banks and car companies. A typical negative idiosyncratic shock to banks results in one-time fall in the bank's equity price by 10%, increases its CDS spread by 9 basis points and increases its one-year default probability by 0.05%. The effects of an idiosyncratic shock to a car company are very similar. A negative idiosyncratic shock reduces its equity price by 11 %, increases its CDS spread by 8 basis points and increases its default probability in one year time by 0.03 %. While we do not find any evidence that certain characteristics of the firms exacerbate the short-term effects of an idiosyncratic shock, we do find that such shocks have medium-term implications for the firms' liquidity and leverage ratios, and price-to-book value. Furthermore, we find mixed results for the granularity of idiosyncratic shocks in the short-term. Such shocks have a significant effect on the equity price index of the sector and result in a significant change in the VIX and the Dollar-Euro exchange rate in response to a *negative* idiosyncratic shock. Further analysis of the granularity of the shocks is still needed.

The paper is organized as follows. After a literature review in Section 2, Section 3 presents the data. Section 4 explains our identification scheme to construct a database of idiosyncratic events for banks and car companies. Section 5 describes the empirical model, which is used in Section 6 to investigate the granularity and the effects of these events on firms' own market

valuation and the spill-overs to the firms in the same sector in the short- and medium-term. Section 7 concludes.

2 Literature review

Our work is most closely related to the empirical literature on contagion and its channels among financial institutions. Jorion and Zhang (2009) have started the empirical literature on credit contagion from counterparty risk, even though they include debtors from all industries, not only banks. They show that a bankruptcy announcement leads to an increase in negative abnormal equity returns and credit default swap (CDS) spreads for the creditors, with the intensity of the effect highly related to the respective credit exposure. Helwege and Zhang (2016) build on their approach, but focus explicitly on the effect of bankruptcy announcement and other distress events from troubled financial institutions. Their results indicate that both counterparty and information contagion have a significant effect, even though the magnitude is rather modest. Gropp et al. (2009) have introduced a cross-border dimension on spillovers, by showing that cross-border contagion among large banks in Europe exists, but without investigating the transmission channels. Chan-Lau et al. (2012) use an extreme value theory framework to show that contagion among global financial institutions displays a strong home bias effect. Furthermore, contagion seems to be stronger in more turbulent times than in calm periods. Mink and de Haan (2014) analyse empirically the effect of default risk changes of G-SIFIs, measured as changes of CDS spreads or expected default frequency (EDF) on the market valuation of other banks. They show that the change of default risk of an individual G-SIFI doesn't seem to have a significant systemic impact, but that G-SIFIs as a group indeed have. Nevertheless, their methodology does not explicitly differentiate between idiosyncratic and common shocks, so that the direction of causality remains unclear.

We also relate to a large literature on contagion and financial networks, even though it is mainly of theoretical nature. One part of this literature analyses the effect of the overall financial network structure on the severity of contagion effects. With their seminal paper, Allen and Gale (2000) initiated this strand of literature, arguing that an incomplete system leads to more fragility. Accordingly, a higher degree of risk exposure diversification is related to a more stable financial system. Subsequent papers have increasingly questioned this argument, pointing to the fact that a more complete financial network with numerous counterparties and

interconnections can have ambiguous effects on systemic risk and that stronger connectedness is not necessarily a synonym for contagion (see Allen and Babus (2009) for a comprehensive overview, Elliott et al. (2014), Glasserman and Peyton Young (2015), Acemoglu et al. (2015), Battiston et al. (2012)). Network analysis has become a popular tool for empirical analyses of financial systems, as it allows the modeling of connections and interactions (see e.g. Minoiu and Reyes (2011) for an application to the global banking system, and Chinazzi et al. (2013) for a post-mortem examination of the international financial network). As mentioned before, we believe that the structure of the network is only one of the possible elements that are needed to understand contagion and financial interconnectedness, because other, less tangible factors (expectations, market psychology) are likely to play a large role in financial markets.

Another strand of the literature has focused on the underlying transmission channels of contagion. Traditionally, direct links among financial institutions are associated with increased counterparty risk, e.g. through cross-holdings of deposits (Dasgupta (2004); see Upper (2011) for a comprehensive overview of contagion in interbank markets), as well as cross-holdings of shares and debt (Elliott et al., 2014). Spillovers might also occur through information contagion, which implies that default or news of distress induce investors to update their assessment of related securities and similar financial institutions. Several authors argue that information contagion is usually of a negative nature, as e.g. spillovers of adverse information of other financial institutions increase borrowing costs (Acharya and Yorulmazer, 2008). Allen et al. (2012) show theoretically that clustered asset structures of financial institutions increase the likelihood of information contagion and are highly dependent on the banks funding maturity and asset structure. However, news of distress at one bank might also imply positive effects for a competitor, as e.g. the bankruptcy of a large financial institution could lead to additional market share (Helwege and Zhang, 2016). Finally, contagion can also spread through indirect channels, in the form of liquidity spirals and fire sales (Shleifer and Vishny, 2011; Caballero and Simsek, 2013).

Finally, in the aftermath of the financial crisis, a large literature has emerged on systemic risk, its measurement and the role individual banks play for the systemic risk of a financial system. Numerous measures have been proposed to quantify the contribution of individual banks to systemic risk, with the CoVar approach (Acharya et al., 2010; Adrian and Brunnermeier, 2016), the marginal expected shortfall (Acharya et al., 2010) or the market-data related approach

of Huang et al. (2012) being prominent examples.² These papers try to develop measures of systemic importance that properly account for the financial interconnectedness of a bank, whereas we try to understand the repercussions of this interconnectedness in form of spill-over effects.

3 Data

Our study of the effects of idiosyncratic shocks is based on a comprehensive sample for the banking and the automobile sector, which is composed of 31 global systemically important banks (G-SIBs) and of 13 of the world's largest car manufacturers. Table 2 provides the complete list of banks and carmakers in our sample as well as the country they are incorporated in. As indicated in greater detail in Table 3, this study relies on daily data for equity returns on firm-, country- and sector-level and the VIX as a measure of global risk in order to identify idiosyncratic shocks to banks and car companies. The country-specific equity price index is the stock market index of the country the firm is incorporated in. For the equity price index of the sector, we take the MSCI World Banks Index and the MSCI World Automobiles Index, which include the stocks of a total of 91 banks and 23 automobile companies. In the following analysis of the granularity of the identified shocks we look at four macroeconomic variables at daily frequency, that is the VIX, the global equity price index for the respective sector as well as the US Dollar-Euro exchange rate and US Dollar nominal effective exchange rate. The firm-specific variables under study comprise the firms' daily equity returns, 5-year CDS spread and one-year default probability. In order to minimize the influence of outliers in the data, we winsorized the top and bottom 1% of the CDS spreads and the default probabilities across the sample. For equity prices, we use the log returns in the regressions. In our analysis of the medium-term effects of the shocks we consider the firm's liquidity and leverage ratio, their price-to-book value and return-on-equity, all at a monthly frequency. The liquidity ratio for car manufacturers is defined as cash and equivalents in percent of total current assets, while for banks it is cash and securities in percent of total deposits. For the leverage ratio we take the commonly used debt-to-equity ratio. The price-to-book value is the firm's share price divided by the book value per share and the return-on-equity is the net income as a percentage of the average common equity in the previous and current year. The data cover the time period from January 2000 to August 2019 and our main

²See Benoit et al. (2013), Biais et al. (2012) and De Bandt et al. (2012) for comprehensive overviews.

data provider is Datastream.

Table 2: List of firms in our sample

<i>N</i>	<i>Car company</i>	<i>Country of incorporation</i>	<i>Bank</i>	<i>Country of incorporation</i>
1	Bayerische Motoren Werke AG	Germany	Agricultural Bank of China	China
2	Daimler AG	Germany	Bank of America	United States
3	Fiat Chrysler Automobiles N.V.	Italy	Bank of China	China
4	Ford Motor Co	United States	Bank of New York Mellon	United States
5	General Motors Co	United States	Barclays	United Kingdom
6	Honda Motor Co	Japan	BNP Paribas	France
7	Hyundai Motor Co	South Korea	China Construction Bank	China
8	Nissan Motor Corp	Japan	Citigroup	United States
9	Peugeot SA	France	Credit Suisse	Switzerland
10	Renault SA	France	Deutsche Bank	Germany
11	Suzuki Motor Corp	Japan	Goldman Sachs	United States
12	Toyota Motor Corp	Japan	Groupe BPCE	France
13	Volkswagen AG	Germany	Groupe Crédit Agricole	France
14			HSBC	United Kingdom
15			Industrial and Commercial Bank of China Ltd	China
16			ING Bank	Netherlands
17			JP Morgan Chase	United States
18			Mitsubishi UFJ FG	Japan
19			Mizuho FG	Japan
20			Morgan Stanley	United States
21			Nordea	Finland
22			Royal Bank of Canada	Canada
23			Royal Bank of Scotland	United Kingdom
24			Santander	United States
25			Société Générale	France
26			Standard Chartered	United Kingdom
27			State Street	United States
28			Sumitomo Mitsui FG	Japan
29			UBS	Switzerland
30			Unicredit Group	Italy
31			Wells Fargo	United States

Table 3: Description of variables

<i>Variable</i>	<i>Variable Name</i>	<i>Source</i>	<i>Notes</i>
$r_{i,t}^c$	Equity returns	Datastream	Log returns in %
r_t^s	Global equity price index for the sector	Datastream	Log returns of MSCI World Banks Index and MSCI World Automobiles Index in %
r_t^c	Local stock market index	Datastream	Log returns of the total stock market index for the firm's country of incorporation in %
$vi x_t$	Global volatility index	Datastream	Chicago Board Options Exchange Market Volatility Index (VIX)
$posE_{i,t}$	Positive event	Authors' calculation	Binary variable taking the value 1 based on (i) an econometric identification of large idiosyncratic movements in daily equity returns and (ii) narrative evidence supporting a firm-related origin of the shock and 0 otherwise.
$negE_{i,t}$	Negative event	Authors' calculation	Binary variable obtained using the same two-step procedure as for the identification of positive events.
$USDEUR_t$	Dollar-Euro Exchange Rate	Datastream	Euro per US Dollar
$USDNEER_t$	USD NEER	Datastream	US Dollar Nominal Effective Exchange Rate
$CDS_{i,t}$	CDS spread	Datastream	Senior 5 Year Credit Default Swap - Mid Spread. 99% Winsorization
$default_{i,t}$	One-year default probability	Bloomberg	Probability of default of the issuer over the next year in % as calculated by the Bloomberg Issuer Default Risk model. 99% Winsorization
$liqu_{i,t}$	Liquidity Ratio	Datastream	For industrials: Cash & equivalents as % of total current assets. For banks: Cash & securities as % of total deposits
$lev_{i,t}$	Leverage Ratio	Datastream	Debt as % of common equity
$PTBV_{i,t}$	Price to Book Value	Datastream	Share price divided by the book value per share
$ROE_{i,t}$	Return on Equity	Datastream	Net income as % of the average of last year's and current year's common equity

4 Identifying idiosyncratic shocks to global banks and carmakers

In order to analyse the spill-over effects of idiosyncratic shocks, we require a proper identification of exogenous events that have affected individual firms either positively or negatively, without having a direct effect on other firms in the sector. To do so, we mean to identify idiosyncratic shocks to global banks and car companies by adopting a two-step procedure which is based on (i) the determination of large idiosyncratic movements in equity returns and (ii) narrative

evidence confirming a firm-specific origin of the shock. While the first step of our identification strategy relies on a purely econometric methodology, the second step adds narrative information. This is essential in order to ensure to clearly isolate events which are not driven by common macroeconomic shocks but are indeed idiosyncratic. Hence, only if both numerical and narrative requirements are satisfied, we define an event.

4.1 Econometric Identification

For the first part of our shock identification procedure we estimate the residual component of equity returns which cannot be explained by common financial market movements, both at a global and national level. We estimate a linear panel model for the banking and automobile sector respectively, regressing the log returns of the daily stock price of each firm in the sector on a number of controls:

$$r_{i,t}^c = \beta_0 + \beta_1 r_t^s + \beta_2 r_t^c + \beta_3 r_t^{avg} + \beta_4 vix_t + \beta_5 r_{i,t-1} + \beta_6 r_{i,t-2} + \epsilon_{i,t}, \quad (1)$$

where $r_{i,t}^c$ is the daily equity returns of firm i incorporated in country c at time t , r_t^s is the log returns of the global sector-specific equity index, $r_{t,i}^c$ is the log returns of the equity index for the firm's country of incorporation, r_t^{avg} the average equity returns across the sample for the sector and vix_t the global stock volatility index. Based on the fitted model, we calculate the residuals $\epsilon_{i,t}$ to obtain the component in equity returns that cannot be explained by common market movements and that is specific to firm i . We then calculate the standardized residuals $\epsilon_{i,t}^{std}$ of the residuals $\epsilon_{i,t}$ using the rolling standard deviation of the last 50 business days, which corresponds approximately to the past two months. This also ensures that episodes are approximately uniformly distributed in the sample and do not cluster, in particular during the global financial crisis. In the following, we use these standardized residuals $\epsilon_{i,t}^{std}$ to identify shocks on the basis of a purely econometric identification methodology as a first step. This will then be augmented with narrative evidence in the second step.

We define two dummy variables $posE_{i,t}$ for positive and $negE_{i,t}$ for negative events using the standardized residuals $\epsilon_{i,t}^{std}$ from equation 1. The event dummies take the value 1 or 0 on the basis of three criteria which are related to the (i) size, (ii) idiosyncrasy and (iii) consistency of the shocks (see Table 4). First, we only want to capture days with very large positive or negative

movements in the regression residuals, i.e. “jumps”, since these days are more likely to contain firm-specific information as opposed to common market news. The variable $posE_{i,t}$ thus assumes a value of one on the condition that the standardized residual is greater than seven and is set to zero otherwise. Symmetrically, for the variable $negE_{i,t}$ to take the value one, the standardized residual must be lower than minus seven, else it is zero. Note that we choose the 7 standard deviations outliers based on the empirical distribution of the residuals $\epsilon_{i,t}$, which shows to be highly non-Normal and having fat tails. Second, in order to ensure idiosyncrasy, we put the general constraint that only one firm in the sample for the sector can have an event of the same sign on any given day, otherwise the event dummy is set to zero for all firms. This criterion, however, is cross-checked against narrative information in order to avoid dropping events that are idiosyncratic but involve more than one firm. As the third requirement, we impose that the change in the share price on any day of an event has to be consistent with the sign of the event. Hence a positive event has to involve a positive change in the firm’s share price, while on a day of a negative event the change needs to be negative. In the given sample, this third criterion does not restrict our sample of identified shocks. Note that we do not place any restrictions on the reactions of the other firms in the sector. Only if the three requirements are fulfilled, the event dummy is set to one in the first step of our identification procedure.

On the basis of this first step of our shock identification strategy, we recover 55 events for the car industry, 25 negative and 30 positive ones. For the banking industry, we identify 77 negative and 30 positive events, which makes a total of 107. For the sake of brevity we do not report the full list of events but only the events for which we find narrative evidence (see Table A.1 & A.2 in the Appendix).

Table 4: Criteria for the definition of a shock

<i>Criterion</i>	<i>posE_{i,t} = 1 if</i>	<i>negE_{i,t} = 1 if</i>
(i) Size	$\epsilon_{i,t}^{std} > 7$	$\epsilon_{i,t}^{std} < -7$
(ii) Idiosyncrasy	$posE_{j,t} \neq 1$	$negE_{j,t} \neq 1$
(iii) Consistency	$r_{i,t} > 0$	$r_{i,t} < 0$

4.2 Narrative Identification

In the second step of our identification strategy we collect narrative evidence on the origins of the events identified in the first part. Our aim thereby is to disentangle events which are predominantly driven by common market factors from firm-specific news such as, say, profit reports, announcements of restructuring plans or the uncovering of scandals. Only the latter type of shocks are included in our database of shocks since we look for large idiosyncratic movements in equity returns that can be explained by non-aggregate events. For this reason we drop events which take place on days that are marked by news about major global or regional economic and political events such as the global financial crisis or the Brexit vote. As our main sources for narrative information serve the firms' press releases and press reports published by the Financial Times and Bloomberg concerning the respective firm around the identified event days. We choose these sources of information as they are most widely available sources of information on financial news for equity traders and market participants.

We distinguish in particular between four types of shocks which may either be positive or negative, that is shocks related to (i) earnings announcements, (ii) investment news, (iii) M&A activities and (iv) operations- and staff-related news which may include management changes as well as accusations of misconduct and scandals. More specifically, shocks related to earnings announcements generally involve reports of the firms' latest results or profit forecasts. Events based on investment news are linked to the firms' financing operations, hence it includes announced and realized share issuance or buybacks as well as new partnership agreements with other firms. To the third category we assign events that are based on M&As, spin-offs or the restructuring of the firm in general. The last category comprises shocks provoked by changes in management as well as accusations of misconduct and scandals. Table 5 reports the total number of shocks grouped under each of the four categories.

For the 55 shocks in our sample for the automobile industry, 52 could be ascribed to a firm-related event. The full list of events including a brief description of it is found in Table A.1 in the Appendix. Using the proposed categorisation of shocks as shown in Table 5, the main causes for negative events to car companies are announcements of lower profit results and news on scandals, while positive events are mostly driven by announcements of large profit increases or restructuring plans.

For the banking industry, we found narrative information for 82 of the 107 events. Table A.2

in the Appendix contains the complete list and description of the identified events for banks. We omitted a total of 25 event days as they were caused by rumors, global events or no specific origin could be identified at all. Among these were, for example, five negative events that fell into very volatile periods marked by the global financial crisis in 2008. Also dropped were country-specific political events such as the US presidential elections in November 2016, which prompted a general increase in demand for safe-haven stocks of Swiss corporations, the Brexit Vote in June 2016 or the agreement on a provisional Brexit deal between the UK and the EU in November 2018, both of which were followed by a general fall in share prices of British corporations. In general, negative events in the banking sector were often sparked by announcements of losses and accusations of misconduct. Prominent examples in our shock database are the UBS rogue trader scandal in 2011 or the Libor scandal in 2013. Positive events were mostly the result of positive profit reports or restructuring plans.

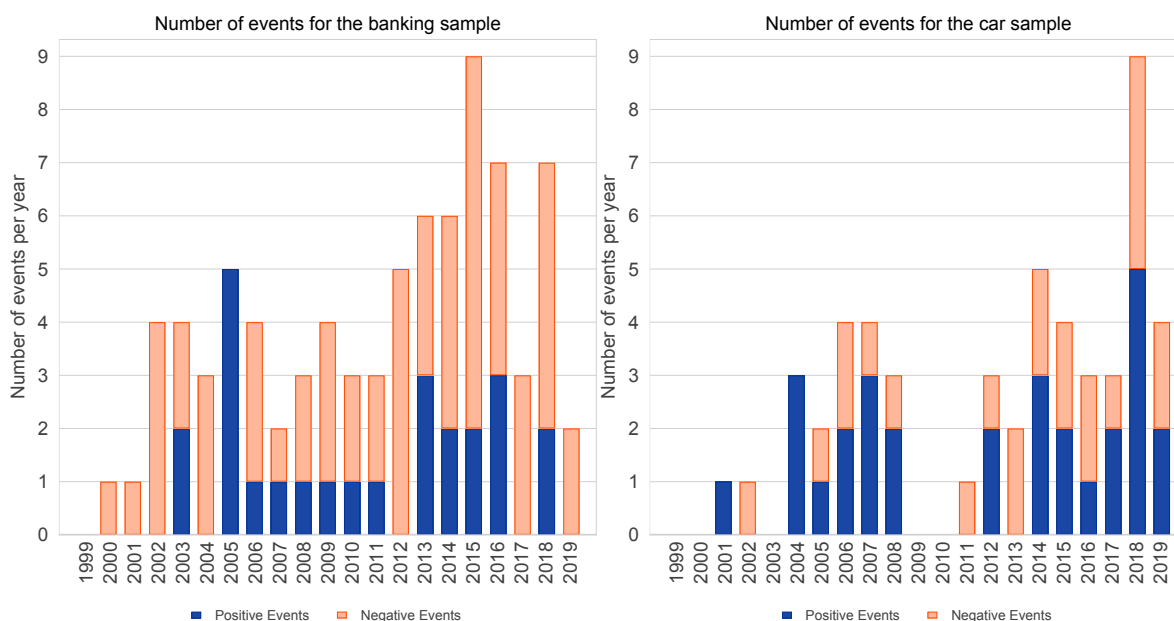
Table 5: Types of shocks

Type of shock	<i>Car Companies</i>		<i>Banks</i>	
	Positive	Negative	Positive	Negative
(i) Earnings	16	17	20	33
(ii) Investment	5	-	1	4
(iii) M&A	6	-	4	6
(iv) Operations	2	6	-	14
Omitted	1	2	5	20
Total	30	25	30	77

4.3 Characteristics of the idiosyncratic shocks in the sample

Figure 1 provides an overview of the distribution of events for banks and car companies in our sample period from 1999 until August 2019. We do not observe any strong clustering of events around 2008 and 2009 during the peak of the global financial crisis. The missing clustering of events may be ascribed to the conservative approach we take in our shock identification strategy. To make sure that we only uncover events that are truly idiosyncratic and not driven by common macroeconomic shocks, we impose the restriction that only one firm in the sample for the sector can have an event of the same sign on any given day. In terms of frequency over time, we note an increase in the number of events for banks in the last years of our sample period and in the year 2018 for car companies especially, which is unsurprising.

Figure 1: Number of events for global banks and carmakers over time



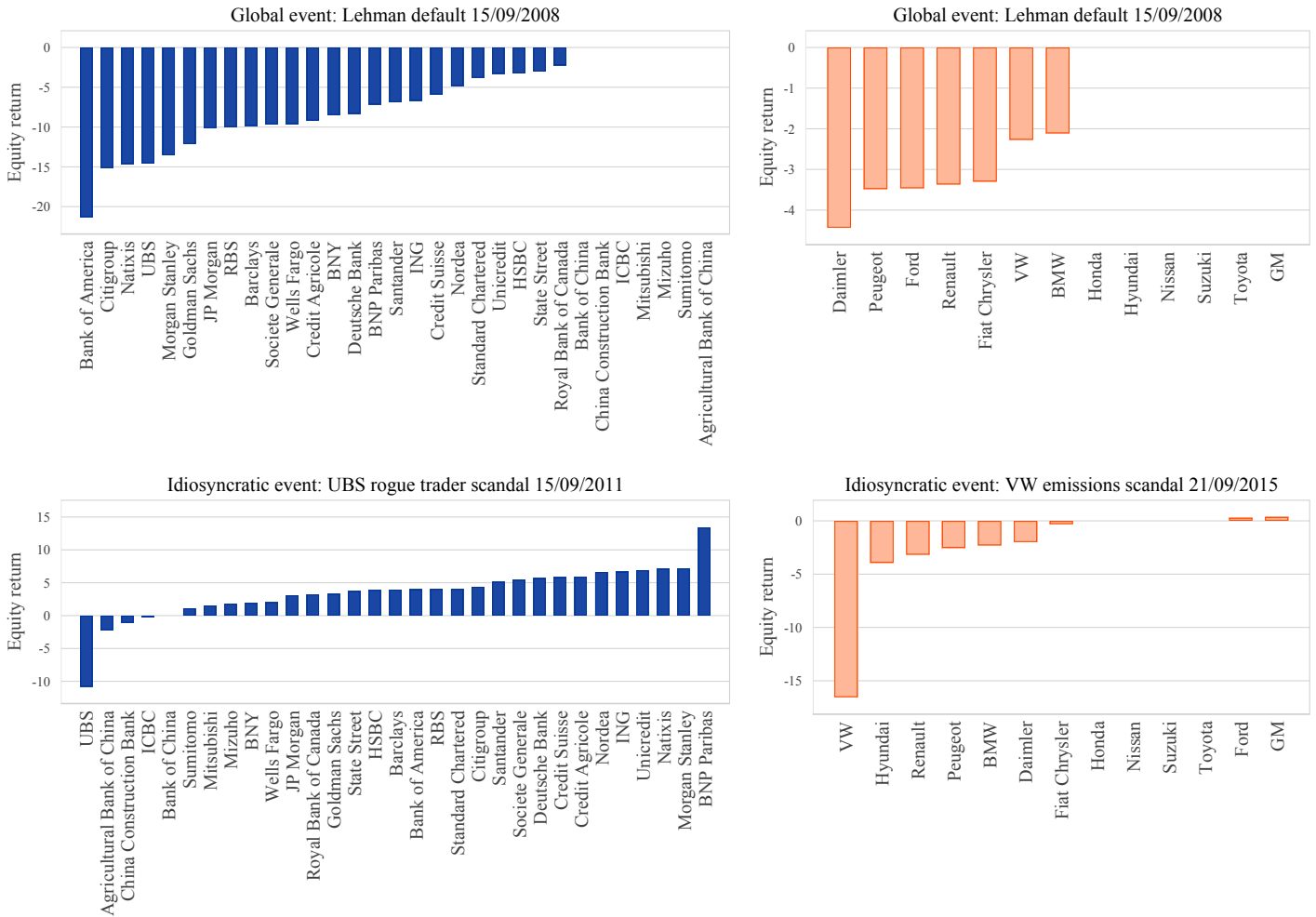
Notes: Total number of identified events in the sample for global banks and car makers per year.

Looking at the average effect of the identified events on firms' equity returns on the day of the event confirms the importance of the identified shocks for the firm that is directly affected. A positive event ($posE_{i,t} = 1$) leads, on average, to a rise in the equity return of the bank where the shock originates by 14.4%, while the returns of the other banks in the sample for the sector increase by 0.9%. In the case of a negative event ($negE_{i,t} = 1$), the corresponding change in equity return amounts to -11.1% for the bank receiving the shock and -0.2% for the other banks in the sample. As for car companies, a positive event results in a rise of the company's own equity return on average by 14.0% and by 0.2% for the rest of the firms in the sample for the automobile sector. A negative event results in a fall in the car company's own equity return by 9.6% and by 0.5% for the other car companies.

It also proves useful to compare the average immediate reaction of firms' equity returns in response to single idiosyncratic shocks compared to global shocks. We therefore look at the firms' equity returns on the day of the default of Lehman in 2008 as an example of a common shock and a representative idiosyncratic event in each sector. The top panels in Figure 2 display the change in equity returns of each firm in our sample for the banking sector on the left and for the automobile industry on the right on the day of the default of Lehman (September 15, 2008).

On that day, 24 of the 31 global banks in our sample saw their equity return fall, on average by 7.1% across the total sample. Average equity returns fell by 1.9 % for car companies in our sample on that day. The bottom left panel shows the equity returns of banks on the day of an identified idiosyncratic shock to UBS, which is related to the rogue trader scandal in 2011. The equity return of UBS fell by 10.8 % on that day, while the equity returns of the other banks in the sample increased on average by 3.9%. The bottom right panel gives the equity returns of car companies on the day of an idiosyncratic shock to VW related to its Diesel emission scandal in 2015. This shock led to a 16.5% fall of VW's equity returns, while the equity returns of other car makers in the sample fell by 1.1% on that day. These numbers suggest that our identified shocks are indeed idiosyncratic as their effect on the market valuation of the directly affected firm is much larger, or even opposite, than for other firms in the same sector. This is not the case for common shocks even when taking into account a certain amount of heterogeneity in the reaction of firms to such shocks.

Figure 2: Response of firms' equity returns to idiosyncratic and global shocks



Notes: Equity returns on specified days sorted by magnitude. Missing bars mean that there has been no change in the firm's equity returns on that day.

5 Estimating the effects of idiosyncratic shocks

We use our database of idiosyncratic shocks to global banks and car companies to assess the effects of such shocks on a number of macroeconomic and firm-specific variables, and the spill-overs to other firms in the same sector. Our panel fixed-effect model estimated as local projections is specified as:

$$y_{i,t+h} = \alpha_i + \lambda_t + \beta_h E_{i,t} + \rho_h y_{i,t-1} + \epsilon_{i,t+h}, \quad (2)$$

where y is a vector of outcome variables and $E_{i,t}$ is the binary event dummy as previously defined, indicating a shock to firm i at time t . We consider a time horizon h from 0 to 20.³ The model includes both firm and monthly time fixed effects such that it is effectively a *difference-in-difference* estimation. The local projection responses of $y_{i,t+h}$ with respect to an event in $E_{i,t}$ is given by the parameter β_h .

The elements of vector y include (i) a set of macroeconomic variables to test for the granularity of the shocks and (ii) firm-specific financial variables to test for their effects on the market valuation of the firm directly affected by the shock and of other firms in the sector. To estimate the granularity of the shocks, we run local projections on four macroeconomic variables, that is the VIX, the log equity index for the respective sector (p_t^s), the US Dollar-Euro exchange rate ($USDEUR_t$)⁴ and the US Dollar nominal effective exchange rate ($USDNEER_t$). The firm-specific variables include the log equity price (p_t), the 5-year CDS spread (CDS_t) and the one-year default probability ($default_t$) of firm i and of the other firms j in the same sector.

We run different panel regressions in which we also distinguish between positive and negative shocks; and different types of shocks according to the four categories outlined in Section 4. This first part of our analysis focuses on the short-term effects and spill-overs of up to 20 days after the shock has occurred. In addition, we also run monthly local projections with a time horizon of up to 12 months after the shock in order to estimate the medium-term implications of the shocks for the firms directly affected. To do so, we sum the number of shocks per firm per month and estimate Equation 2 with a time horizon h from 0 to 12 months and yearly time fixed effects. The variables under study include the firms' liquidity ratio ($liqu_{i,t}$), leverage ratio ($lev_{i,t}$), price-to-book value ($PTBV_{i,t}$) and the return-on equity ($ROE_{i,t}$). The liquidity ratio for car manufacturers is the cash and equivalents in percent of total current assets and for banks it is cash and securities in percent of total deposits. The leverage ratio is defined as debt in percent of common equity.

We use as similar regression specification to check whether certain characteristics influence a bank's vulnerability to idiosyncratic shocks in Section 6.5. The estimated model is again a panel-fixed effect equation,

³To check for the possible anticipation of the shock, we also considered a time horizon h starting at -3 rather than 0 and controlled for $y_{i,t-4}$ in Equation 2.

⁴We use the Dollar-Euro exchange rate because 8 of the 13 car manufacturers and 17 of the 31 global banks in our sample are either incorporated in the United States or in a country of the Euro Area.

$$r_{i,t} = \alpha_i + \lambda_t + \beta E_{i,t} + \gamma X_{i,t-1} E_{i,t} + \delta X_{i,t-1} + \epsilon_{i,t}, \quad (3)$$

where $r_{i,t}$ is bank i 's equity returns and X is a vector of lagged characteristics of bank i . The regression includes again firm and monthly time fixed effects. We are interested in the interaction terms of the respective regressors with our event dummy $E_{i,t}$, so that we specifically test these interaction terms for significance, whereas the non-interacted terms are included as focus variables that are not tested for explicitly. The elements of vector X include the bank's daily price-to-book value ($PTBV_{i,t-1}$), one-year default probability ($default_{t-1}$), liquidity ratio ($liqu_{i,t-1}$) and leverage ratio ($lev_{i,t-1}$). For ease of interpretation, the variables in the X vector are standardised.

6 Results

Before describing our results in greater detail, we start with an overview of our four main findings. First, we find mixed evidence for the granularity of idiosyncratic shocks to individual firms. Idiosyncratic shocks to banks and car companies show to have a significant effect on the equity price index of the sector. We also find a significant change in the VIX and the Dollar-Euro exchange rate in response to a *negative* idiosyncratic shock. Second, we show that idiosyncratic shocks have large effects on the firm's own market valuation. A typical negative idiosyncratic shock to banks results in one-time fall in the bank's equity price by 10%, increases its CDS spread by 9 basis points and increases its one-year default probability by 0.05%. The effects of an idiosyncratic shock to a car company are very similar. A negative idiosyncratic shock reduces its equity price by 11%, increases its CDS spread by 8 basis points and increases its default probability in one year time by 0.03%. While we do not find any evidence that certain characteristics of the firms exacerbate the short-term effects of an idiosyncratic shock, we do find that such shocks have medium-term implications for the firms' liquidity and leverage ratios, and price-to-book value. These medium-term effects differ in terms of their sign and size between the two sectors. Third, some spill-over effects of idiosyncratic shocks to other firms in the sector exist, but they are generally small in size and are more pronounced in response to negative events than to positive ones. Fourth, given that the spill-over effects are very modest, we also do not find any prominent differences in the spill-overs across banks and car manufacturers.

In the following, we turn to describing our results in detail, starting with a brief analysis of the granularity of the shocks (Section 6.1), then moving to our baseline results (Section 6.2), before distinguishing between positive and negative shocks (Section 6.3) and different types of shocks (Section 6.3). We then look at certain firm characteristics that may increase the vulnerability of banks to idiosyncratic shocks (Section 6.5) and how they evolve in response to an idiosyncratic shock in the medium-term in Section 6.6. In all the figures presented in this section, the solid blue lines refer to our sample for the banking sector and the dashed red lines to our sample for the automobile sector. The local projection responses derived from the parameter β_h in Equation (2) are shown with confidence bands at the 90 per cent level.

6.1 Are the shocks granular?

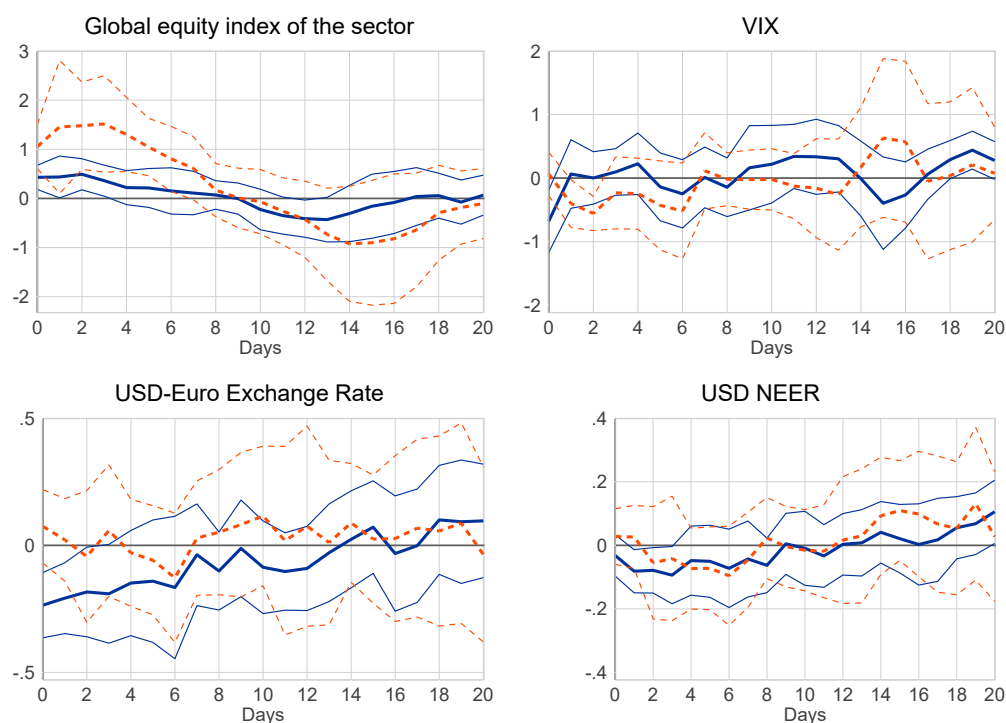
We begin with a brief analysis of the granularity of idiosyncratic shocks by looking at their effects on a set of macroeconomic variables. Specifically, we look at the responses of the global equity index for the respective sector p_{t+h}^s , the VIX_{t+h} , the Dollar-Euro exchange rate $USDEUR_{t+h}$ and the Dollar nominal effective exchange rate $USDNEER_{t+h}$ to an event $E_{i,t}$ at time $t=0$. Note that in this part of our analysis we do not distinguish between the effect following from the firm directly affected by the shock and the spill-over effects on other firms in the same sector.

The results are shown in Figure 3. We find that the shocks have a statistically significant effect on the global equity index of the sector, the effect being stronger and significant for a longer period of time for the automobile sector than for the banking sector. The response of the VIX, the Dollar-Euro exchange rate and the Dollar NEER to an idiosyncratic shock in either of the two sectors is found to be insignificant when we do not further distinguish between positive and negative events. Next we consider the responses of the four macroeconomic variables under study to *negative* and *positive* events only, in order to test for possible asymmetries in their effects. Figure 4 shows the local projection responses of the macroeconomic variables to a negative shock and Figure 5 shows the same local projections in case of a positive shock. Both the global automobile and the global bank equity index only change significantly in response to a positive event. The positive reaction of the global automobile index is stronger than the one of the global bank index, but becomes negative at the end of the considered time horizon. The response of the VIX is negative and significant only in the first few days after a positive shock to the automobile sector. While the Dollar-Euro exchange rate does not change significantly in

our baseline results, the Dollar appreciates modestly against the Euro in response to a negative shock to the banking sector. The response of the Dollar NEER to a negative or a positive shock remains insignificant.

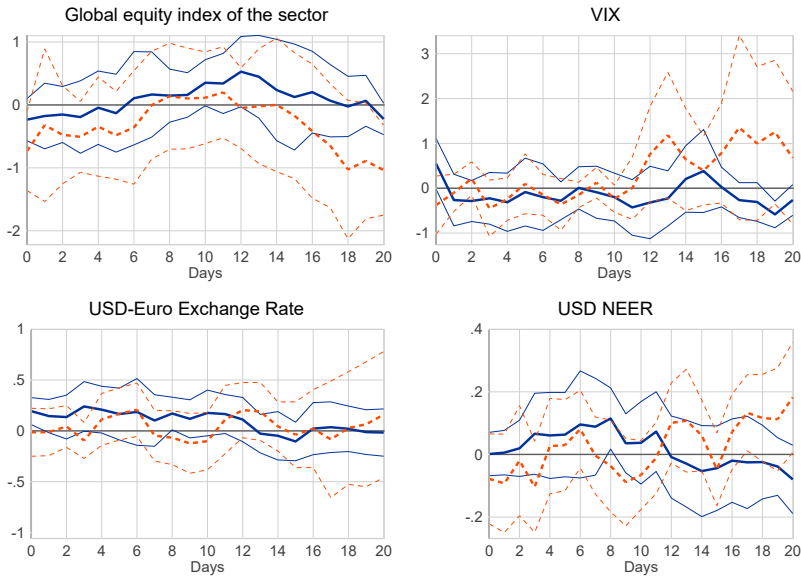
As the focus of this paper is on the firm-specific effects and spill-overs, we limit our analysis of the granularity of idiosyncratic shocks to a few macroeconomic variables, with room for further analysis of the “granularity” of the shocks. This may encompass other exchange rates including the Japanese Yen, the Chinese Renminbi, the British Pound and the Swiss Franc and may benefit from an additional distinction between the effect following from the firm directly affected by the shock and the effect on the other firms in the same sector to gain additional insights into the macroeconomic effects of idiosyncratic shocks.

Figure 3: The granularity of idiosyncratic shocks



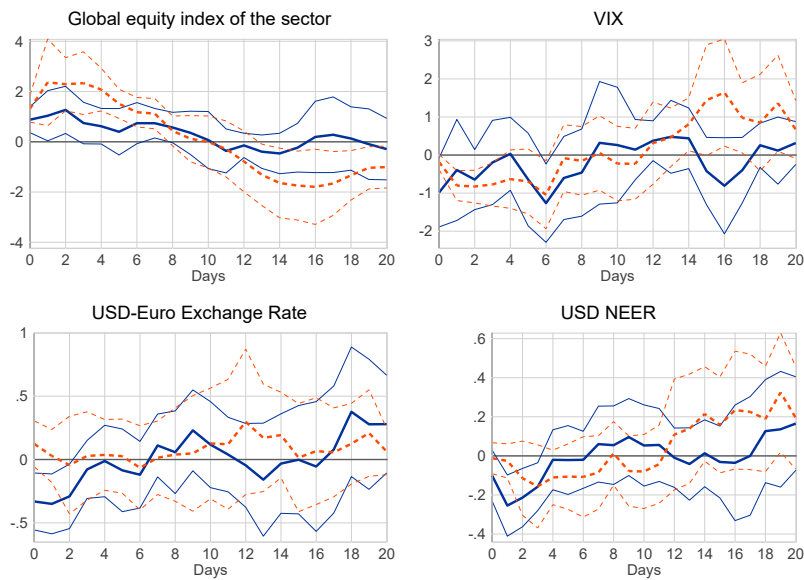
Notes: The figure reports local projection responses derived from the estimated β_h coefficients in Equation (2) for banks in blue and for carmakers in red. The thick line is the local projection response, the thin lines denote the 90% confidence interval and are based on robust standard errors.

Figure 4: The granularity of *negative* idiosyncratic shocks



Notes: The figure reports local projection responses derived from the estimated β_h coefficients in Equation (2) for banks in blue and for carmakers in red. The thick line is the local projection response, the thin lines denote the 90% confidence interval and are based on robust standard errors.

Figure 5: The granularity of *positive* idiosyncratic shocks

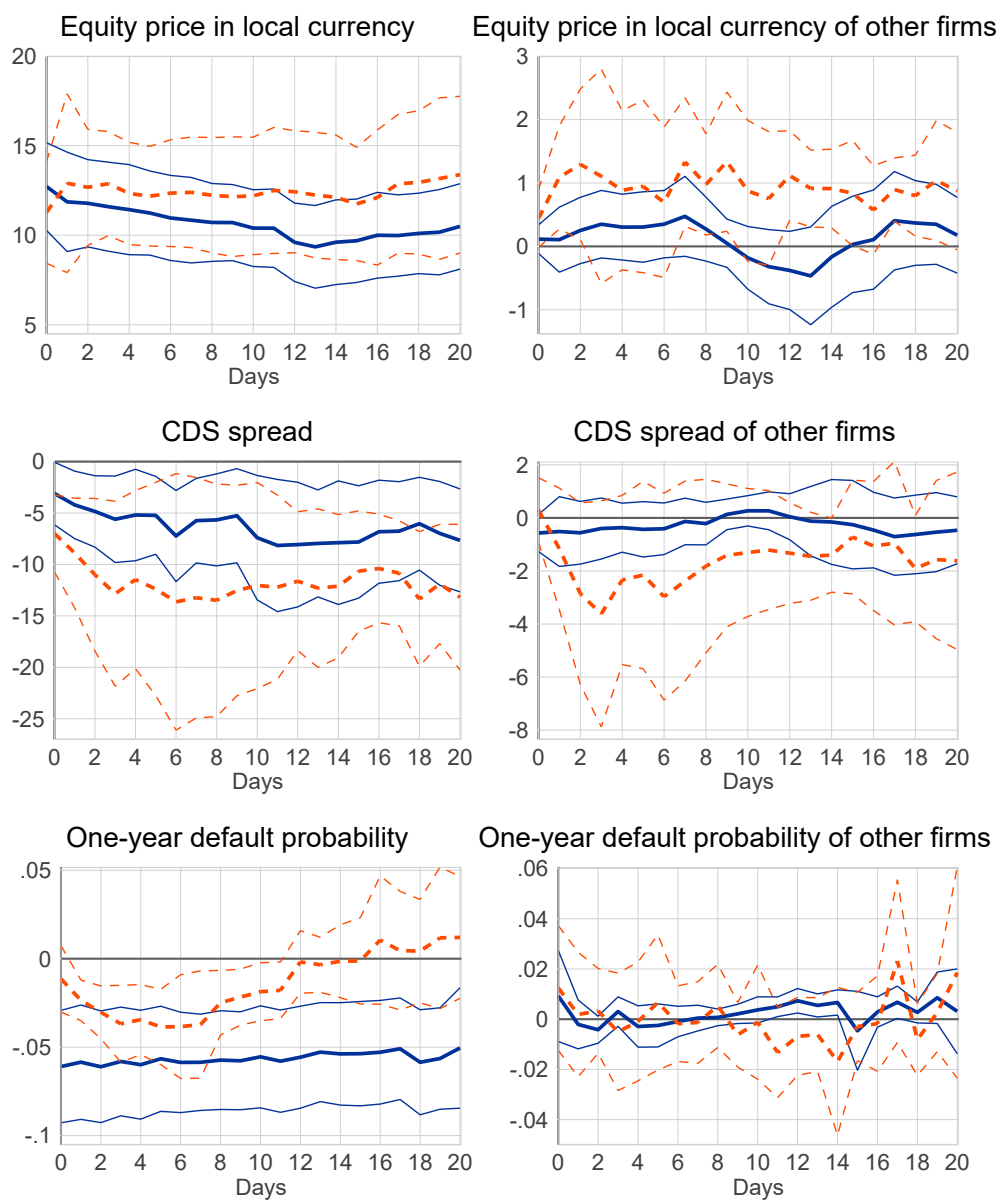


Notes: The figure reports local projection responses derived from the estimated β_h coefficients in Equation (2) for banks in blue and for carmakers in red. The thick line is the local projection response, the thin lines denote the 90% confidence interval and are based on robust standard errors.

6.2 What happens after an idiosyncratic shock?

In our baseline regression we analyse the effects on (i) the log equity price in local currency, (ii) the 5-year CDS spread and (iii) the default probability at one year in per cent for the firm where the shocks originates and for the other firms in the same sector. Note that while we did not make a distinction between the effect following from the firm directly affected by the shock and the effect on the other firms in the same sector in the previous analysis of the granularity of the shocks, we do have this separation in the following local projections involving the firm specific variables. Figure 6 shows the results of our baseline regression specification, which are obtained on the basis of the whole sample of identified idiosyncratic shocks. We find that the shocks have large effects on the firm-specific market variables, whereas the spill-overs to other firms are generally small. An idiosyncratic shock in both the banking and the automobile sector results in a similarly large one-time share price increase of around 11 and 12% on average respectively. An idiosyncratic shock also affects the firm's CDS spread. The average change in the CDS spread observed over the following 20 days in response to an idiosyncratic shock amounts to around 6 basis points for banks and to 12 basis points for car companies. The one-year default probability also changes significantly in response to a shock to a firm of either sector, the effect being larger and significant for a longer period of time for banks than for car companies. The spill-overs to other firms in the same sector in our baseline regression, in contrast, are limited and mostly statistically not significant.

Figure 6: Effects of an idiosyncratic shock



Notes: The figure reports local projection responses derived from the estimated β_h coefficients in Equation (2) for banks in blue and for carmakers in red. The thick line is the local projection response, the thin lines denote the 90% confidence interval and are based on robust standard errors.

6.3 What happens after a positive or a negative shock?

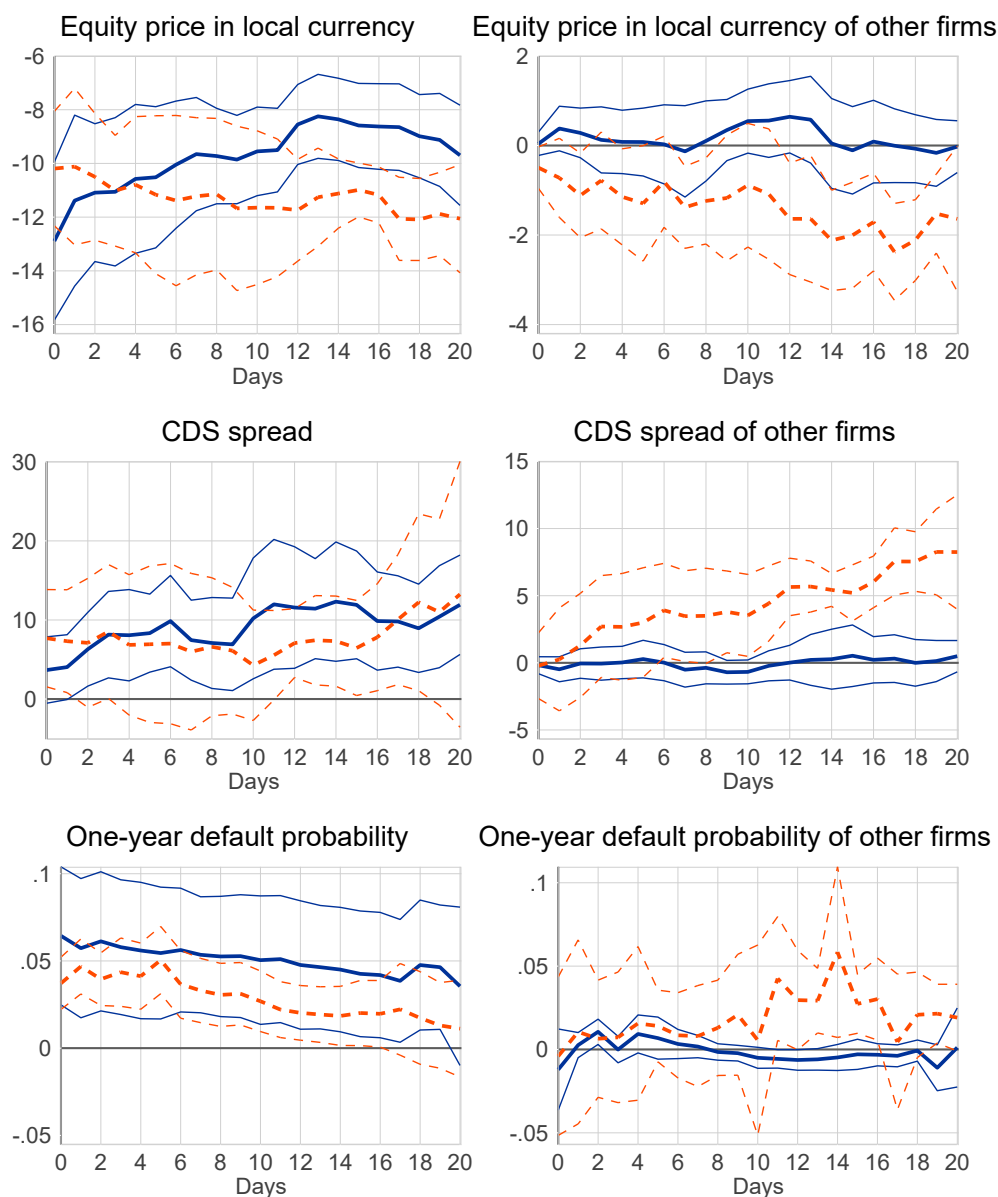
We distinguish between positive and negative events as it could be that the responses to negative events are different, and possibly larger, than to positive events, also because of the prevalence of negative events in crisis periods. Figure 7 and 8 show the local projection responses to negative and positive idiosyncratic shocks respectively. We start with the results for banks. While the change in the bank's equity price is of roughly the same amount in response to a negative or a positive shock, we find that a negative shock has a much larger effect on the bank's CDS spread than a positive one. The default probability changes also symmetrically in case of a positive or a negative shocks to banks. On average, a negative shock reduces the bank's equity price by 10%, increases its CDS spread by around 9 basis points and increases the one-year default probability by 0.05%. A positive event leads to an increase in the bank's equity price by around 13% and the CDS spread does not change significantly, but the default probability is reduced by around 0.07%.

The spill-over effects of negative and positive shocks to other banks are again much smaller than for the bank directly affected by the shock and differ to the baseline results. The average change in equity price for other firms is positive and significant for positive events, amounting to 1% on average in the past 20 days following a shock to another bank. The spill-over effects to CDS spreads and the default probability, in contrast, are not statistically significant for both positive and negative events.

We now turn to the results for the automobile sector. The effect on equity prices differs very little from the baseline results, with an average one-time change in the equity price of 13% following a positive and minus 11% following a negative shock. The CDS spread changes significantly in response to both a negative and a positive shock, on average by minus 15 basis points after a positive event and plus 8 basis points after a negative event. The effect on the default probability remains statistically significant for a longer period of time in the case of a negative shock than a positive shock, increasing the default risk by around 0.03%. As for the transmission of shocks to other car companies, we find that the spill-overs of negative shocks to car companies are stronger than those of positive shocks and slightly more pronounced than in the banking sector. There is a statistically significant effect on equity prices and CDS spreads of other car companies in response to a negative idiosyncratic shock to another car company. A negative shock typically leads to a fall in the other firms' equity prices by 1-2 per cent and the

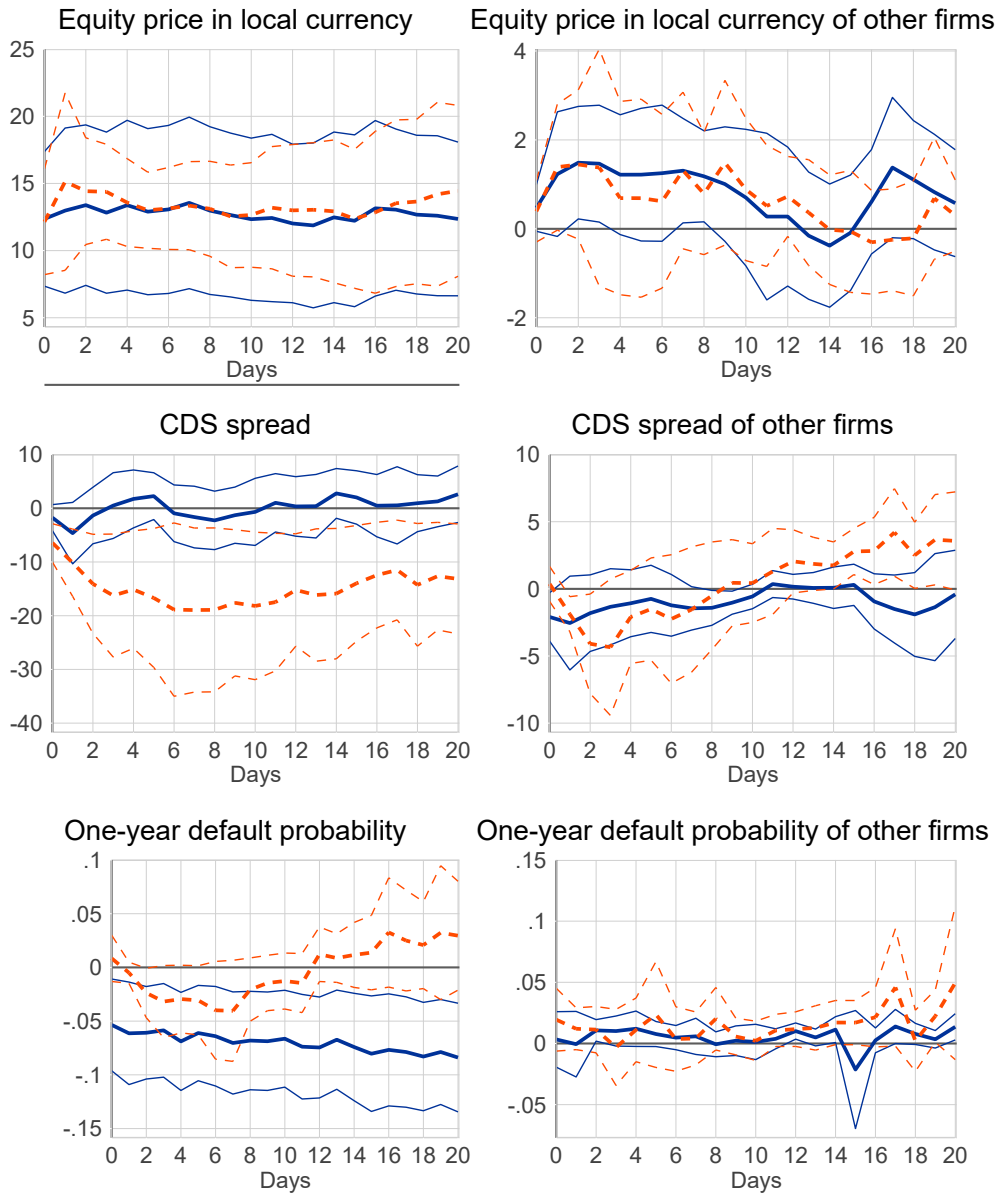
CDS spread increases by approximately 5 basis points. As in the baseline results, the effects of idiosyncratic shocks is much larger for the car company that is directly hit by the shock than for the other car companies.

Figure 7: Effects of a negative idiosyncratic shock



Notes: The figure reports local projection responses derived from the estimated β_h coefficients in Equation (2) for banks in blue and for carmakers in red. The thick line is the local projection response, the thin lines denote the 90% confidence interval and are based on robust standard errors.

Figure 8: Effects of a positive idiosyncratic shock



Notes: The figure reports local projection responses derived from the estimated β_h coefficients in Equation (2) for banks in blue and for carmakers in red. The thick line is the local projection response, the thin lines denote the 90% confidence interval and are based on robust standard errors.

6.4 Effects of different types of shocks

We distinguish between different types of events using the categorisation laid out in Section 4 to check whether the nature of the shock significantly determines the size of its effects. The Figures 9 – 12 show the local projection responses to the four types of shocks, that is shocks related to (i) earnings, (ii) investment decisions, (iii) M&A activities and (iv) operations, scandals and staff changes. We analyse the results in terms of their significance, size, difference to the baseline results and to the other sector.

We begin with the results for equity prices. The effect on the bank's own equity price does not differ greatly given the type of the shock. The effect is significant in all four cases, being the largest in response to investment news (see Figure 10). In the car sector, the average response to a shock related to mergers and acquisitions is with a change of around 25% more than twice as large compared to responses to other types of shocks.

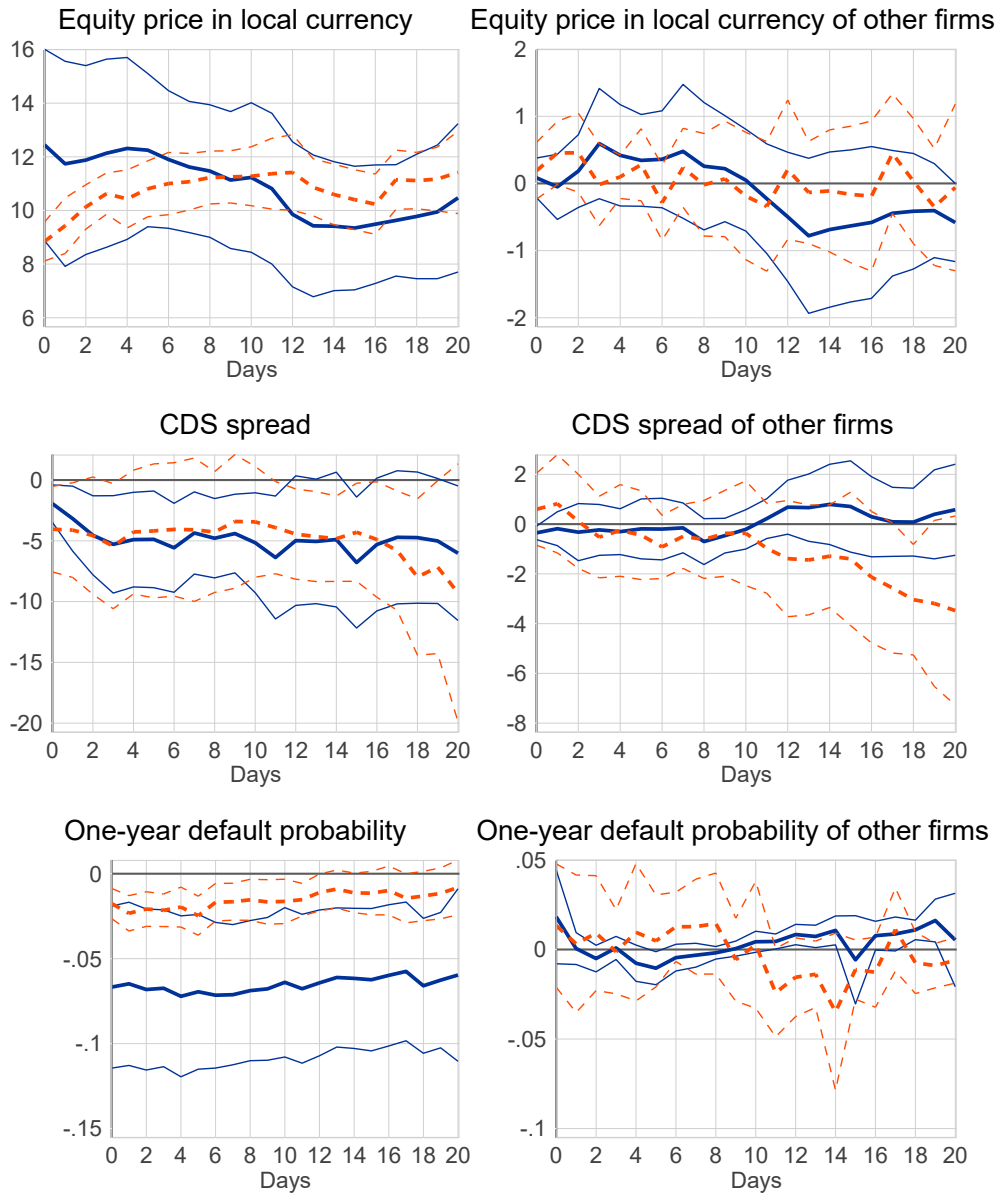
The bank's own CDS spread changes significantly only in response to a shock related to a bank's earnings or operations and staff. In the first case the average response is a change of around 5 basis points, while in the latter the response is much stronger, amounting to around 15 basis points. For the car sector, the change in a car company's own CDS spread is significant in response to all four types of shocks. While there has been a significant change in the one-year default probability in our baseline results for banks, we find a significant change only in response to a shock related to earnings (by around 0.07%) and the bank's operations, staff and scandals (by around 0.4%). Similarly, the default probability of a car company changes significantly in case of a shock related to earnings or operations, staff and scandals. The negative change in response to a shock related to M& A activities only remains significant in the first week after the shock.

We now look at the spill-overs to other firms in the same sector. These are again much smaller than the effects on the company's own market valuation as in the previous results. The effect on equity prices of other banks in the sector is only significant in response to an event related to investment, which leads to a change in equity prices of around 3%. We do not find any statistically strong contagion effects to equity prices in the car sector on the basis of the four types of shocks. The CDS spreads of other firms seem to be affected by the type of idiosyncratic shock. The CDS spreads of other banks change significantly in the case of a shock related to investment and operations, staff and scandals, while there was no general significant change in

the baseline regression or when we distinguished between negative and positive shocks. In the car sector, CDS spreads increase significantly in response to a shock related to investment, but fall in the case of a shock related to M& A or operations, staff and scandals.

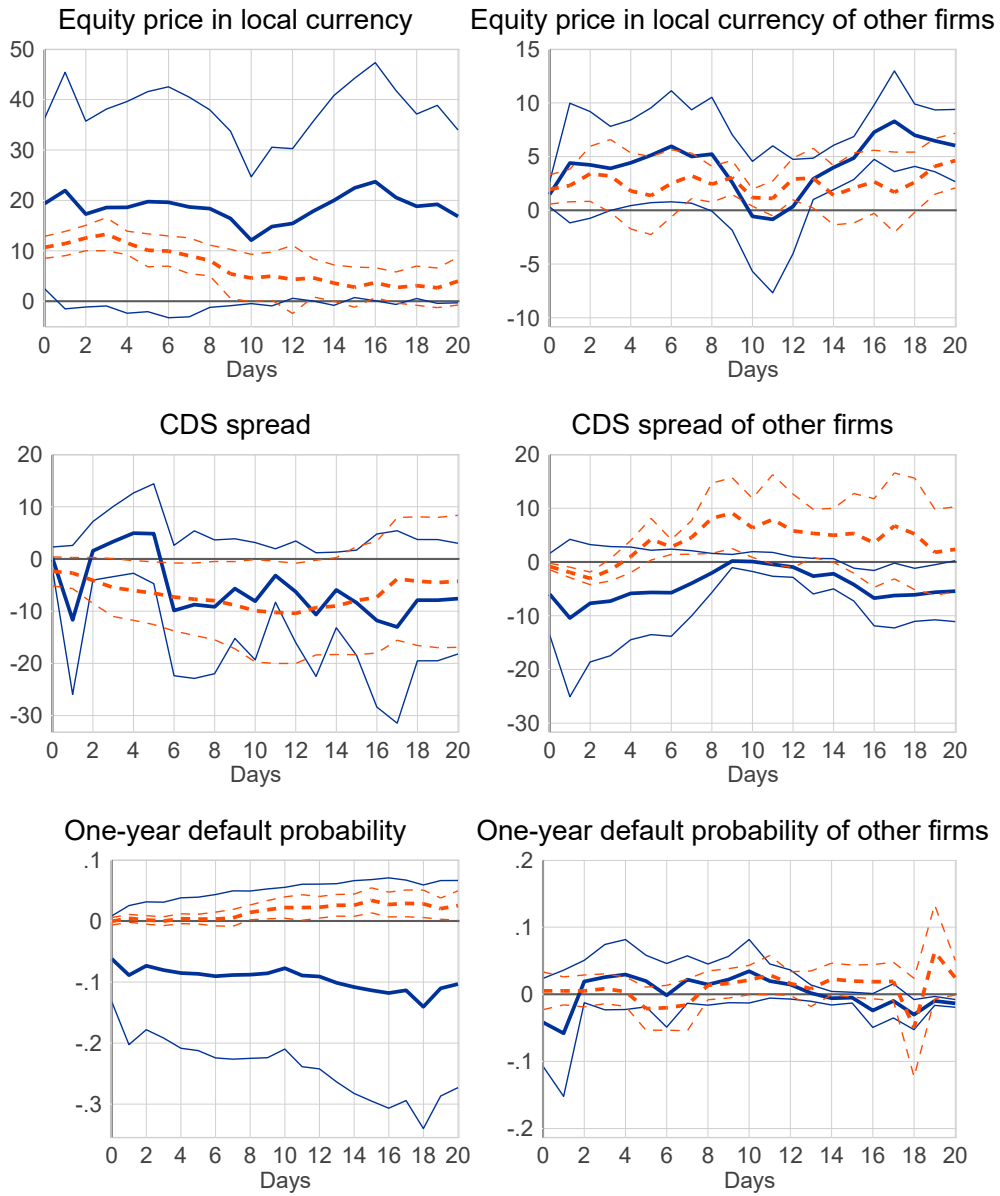
In terms of the one-year default probability, we do not find any significant spill-over effects in the either sector when we distinguish between different types of the events.

Figure 9: Effects of idiosyncratic shocks related to (i) Earnings



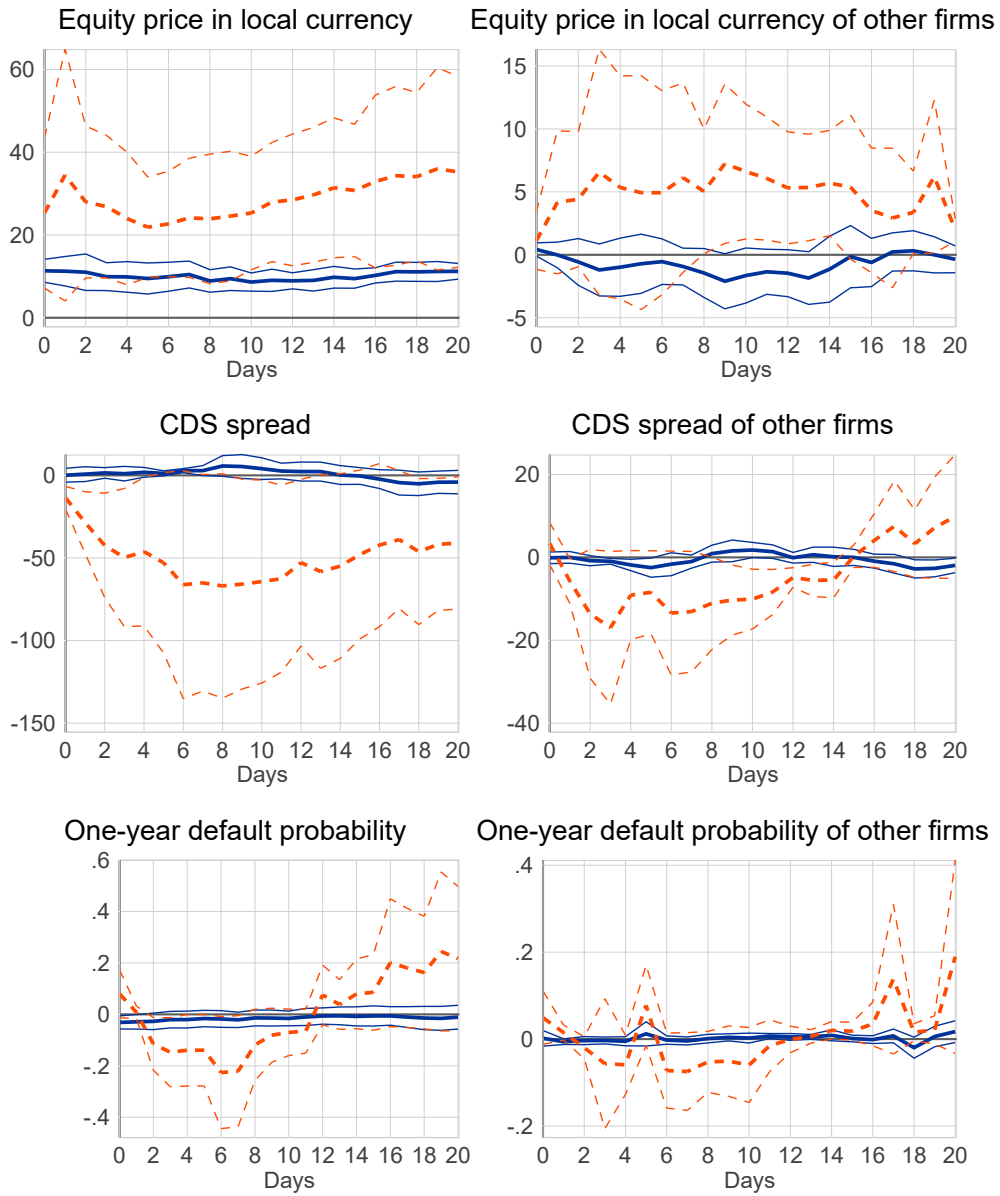
Notes: The figure reports local projection responses derived from the estimated β_h coefficients in Equation (2) for banks in blue and for carmakers in red. The thick line is the local projection response, the thin lines denote the 90% confidence interval and are based on robust standard errors.

Figure 10: Effects of idiosyncratic shocks related to (ii) Investment



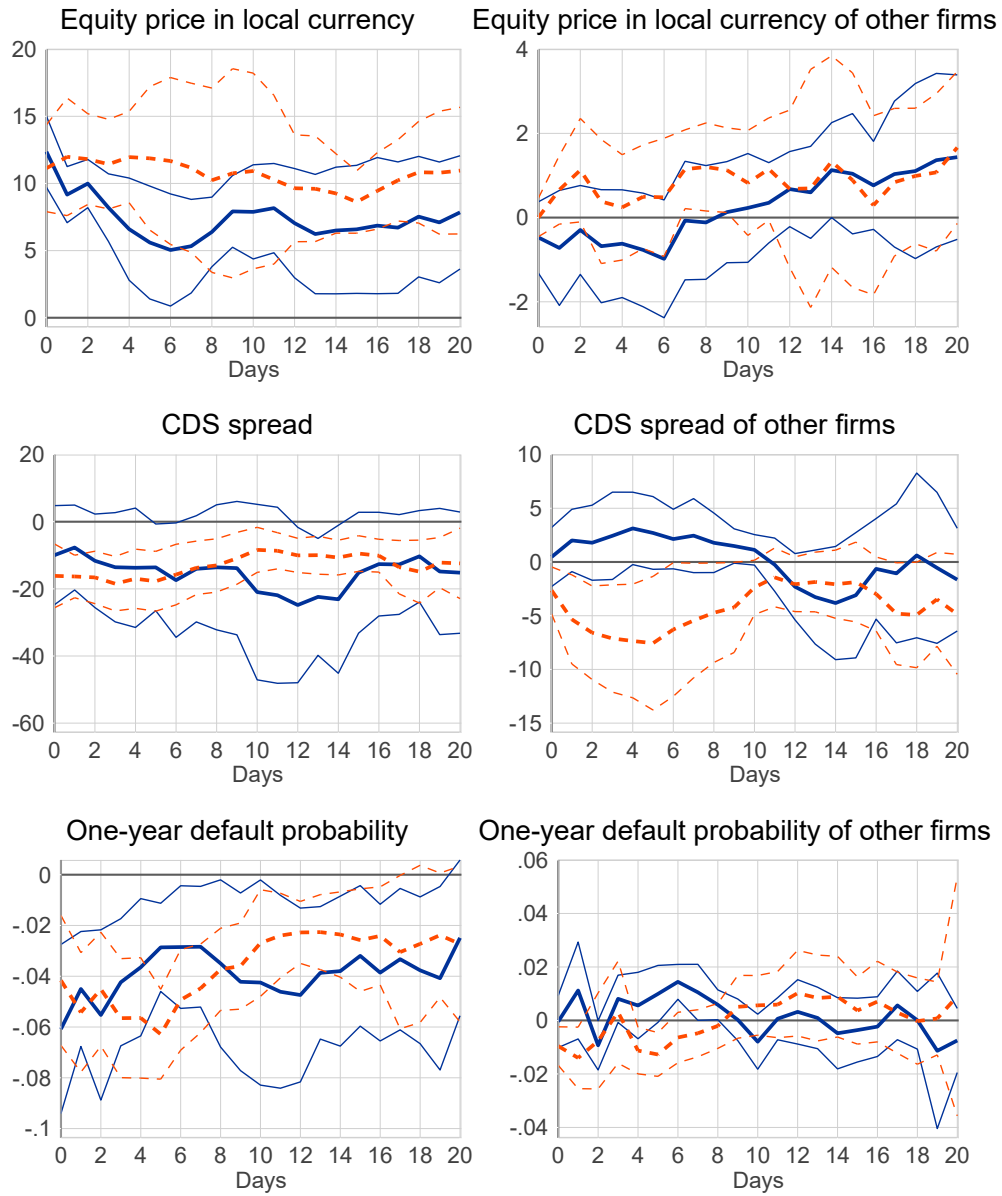
Notes: The figure reports local projection responses derived from the estimated β_h coefficients in Equation (2) for banks in blue and for carmakers in red. The thick line is the local projection response, the thin lines denote the 90% confidence interval and are based on robust standard errors.

Figure 11: Effects of idiosyncratic shocks related to (iii) M&A



Notes: The figure reports local projection responses derived from the estimated β_h coefficients in Equation (2) for banks in blue and for carmakers in red. The thick line is the local projection response, the thin lines denote the 90% confidence interval and are based on robust standard errors.

Figure 12: Effects of idiosyncratic shocks related to (iv) Operations



Notes: The figure reports local projection responses derived from the estimated β_h coefficients in Equation (2) for banks in blue and for carmakers in red. The thick line is the local projection response, the thin lines denote the 90% confidence interval and are based on robust standard errors.

6.5 Firm characteristics for the size of effects

Next we check whether certain characteristics of a bank exacerbate the effects of idiosyncratic shocks. For comparison, we report the regression results of Equation 3 without the vector of lagged characteristics the bank and their interaction with our event dummy in Table 6. Column 1 and 2 give the effect of a negative and positive event on the bank's own equity price, while column 3 and 4 give the effect of an event on the equity price of other banks. 7 reports the results obtained on the basis of Equation 3, including the interaction terms for the shock-originating bank's own characteristics with our event dummy $E_{i,t}$. We report again both the effects of a bank's own event and those of another bank's event in the sector. The characteristics included in the regression comprise the banks' daily liquidity and leverage ratios, price-to-book value and expected default probability at $t - 1$. Looking at the interaction terms of the characteristics of the shock-originating bank, we do not find strong evidence that certain risk and profitability characteristics influence a financial institution's vulnerability to idiosyncratic shocks.

Table 6: Effects of idiosyncratic shocks

	(1)	(2)	(3)	(4)
	Own event	Own event	Other banks' event	Other banks' event
Negative event	-12.898*** (1.787)		-0.052 (0.067)	
Positive event		12.406*** (3.055)		0.962*** (0.095)
Observations	149,735	149,735	149,735	149,735
R-squared	0.026	0.020	0.015	0.016
Number of banks	31	31	31	31
Time FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

Notes: Dependent variable: Daily equity returns, in %.

Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Bank characteristics and the effects of idiosyncratic shocks

	(1) Own negative event	(2) Own positive event	(3) Other banks' negative event	(4) Other banks' positive event
Event	-11.865*** (2.711)	10.776*** (2.105)	0.026 (0.058)	0.836*** (0.090)
Liquidity ratio(t-1)*Event	6.102 (4.329)	-0.896 (0.948)	0.041 (0.060)	0.106 (0.146)
One-year default prob.(t-1)*Event	-18.123 (12.721)	10.575 (6.575)	-0.186*** (0.056)	0.340 (0.228)
PTBV(t-1)*Event	-2.420* (1.318)	1.833 (1.993)	-0.085 (0.107)	-0.406 (0.244)
Leverage ratio(t-1)*Event	2.639 (3.234)	1.010 (2.683)	0.014 (0.093)	0.046 (0.179)
Liquidity ratio(std) t-1	0.008 (0.014)	0.006 (0.015)	0.008 (0.014)	0.008 (0.015)
One-year default prob.(std) t-1	0.056*** (0.010)	0.056*** (0.009)	0.059*** (0.010)	0.053*** (0.009)
PTBV(std) t-1	-0.156*** (0.031)	-0.160*** (0.030)	-0.159*** (0.030)	-0.159*** (0.030)
Leverage ratio(std) t-1	0.026 (0.029)	0.030 (0.028)	0.029 (0.028)	0.029 (0.029)
Observations	122,690	122,690	122,690	122,690
R-squared	0.030	0.022	0.017	0.018
Number of banks	28	28	28	28
Time FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

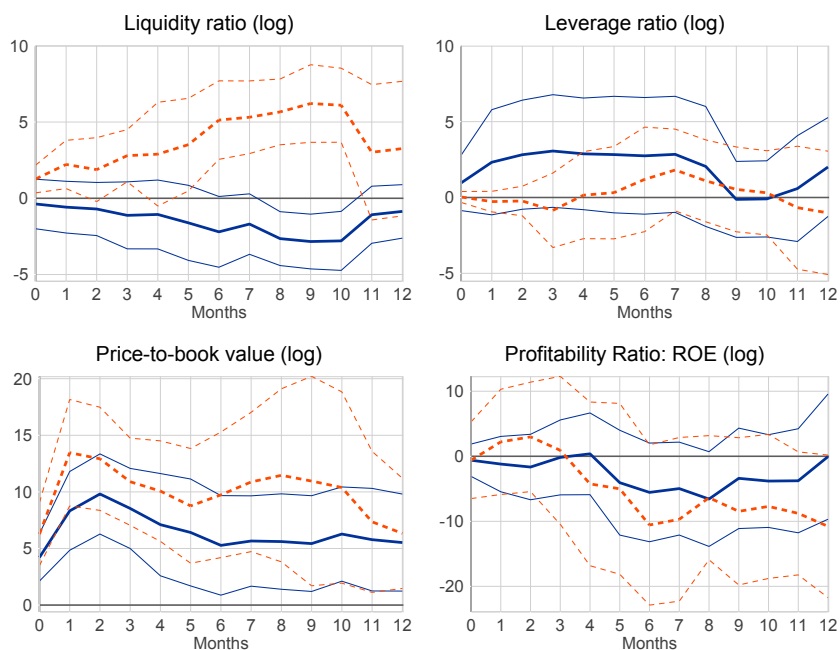
Notes: Dependent variable: Daily equity returns, in %. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

6.6 Medium-term effects of idiosyncratic shocks

We analyse the medium-term effects of idiosyncratic shocks for global banks and car makers by summing the number of events per firm per month and deriving the impulse responses from the estimated β_h coefficients in Equation (2) up to 12 months after a shock. Figure 13 shows the effects of an idiosyncratic shock on the firm's own characteristics, which include the firm's liquidity ratio, leverage ratio, price-to-book value and the return-on equity as a profitability measure. We find that a positive (negative) shock to a bank results in a significant fall (rise) in the bank's liquidity ratio by around 3 %, while its price-to-book value increases (falls) by 6

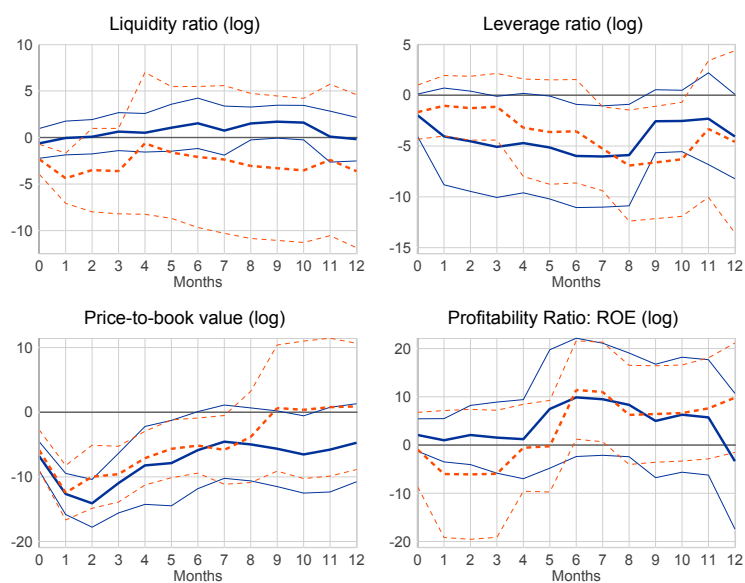
%). In our baseline results, the changes in the leverage ratio and the return-on-equity are not significant for either of the two sectors. In contrast, car companies see their liquidity ratio rise (fall) by around 5% in response to a positive (negative) shock. Their price-to-book value increases (decreases) by 10% on average. As done in the previous analysis, we further distinguish between positive and negative shocks in order to see whether the effects differ depending on the sign of the shock. Figure 14 and 15 show the results for negative and positive shocks respectively. The decrease in the liquidity ratio of banks in response to a positive event is more pronounced than the increase in case of a negative event. The bank's price-to-book value changes significantly in response to both a negative and a positive shock, by around 6% as in the baseline results. Interestingly, we find that the leverage ratio of a bank falls both in response to a positive or a negative shock, by around 5%. The return-on-equity does not change significantly as in the baseline results. For car companies, we observe a significant change in the liquidity ratio only in response to a positive event. In this case it increases by around 7%. The positive change of around 15% in the price-to-book value following a positive event is more persistent than its fall in case of a negative event. The leverage ratio of car companies falls by 5% in response to a negative shock, while the return-on-equity remains unchanged.

Figure 13: Medium-term effects of an idiosyncratic shock on firms' characteristics



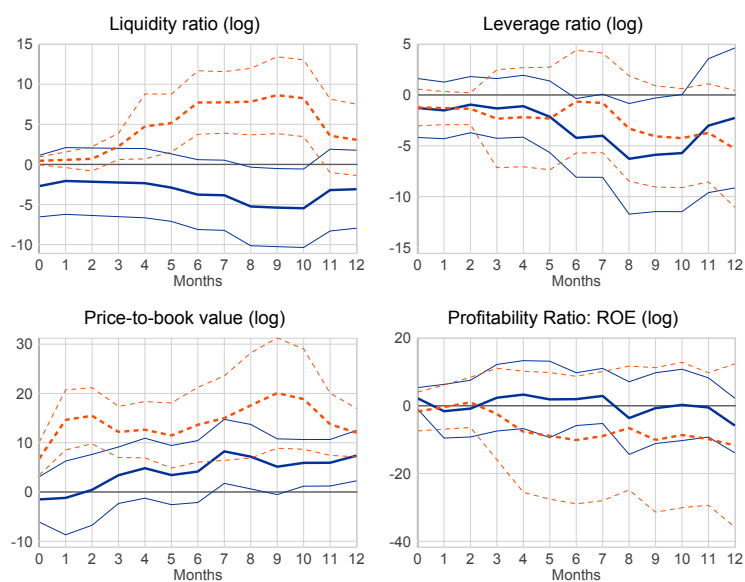
Notes: The figure reports local projection responses derived from the estimated β_h coefficients in Equation (2) for banks in blue and for carmakers in red. The thick line is the local projection response, the thin lines denote the 90% confidence interval and are based on robust standard errors.

Figure 14: Medium-term effects of a negative idiosyncratic shock on firms' characteristics



Notes: The figure reports local projection responses derived from the estimated β_h coefficients in Equation (2) for banks in blue and for carmakers in red. The thick line is the local projection response, the thin lines denote the 90% confidence interval and are based on robust standard errors.

Figure 15: Medium-term effects of a positive idiosyncratic shock on firms' characteristics



Notes: The figure reports local projection responses derived from the estimated β_h coefficients in Equation (2) for banks in blue and for carmakers in red. The thick line is the local projection response, the thin lines denote the 90% confidence interval and are based on robust standard errors.

7 Conclusions

This paper builds a unique database of 134 firm-specific events affecting the expected profitability of two types of large firms, global banks and car producers. The identification approach is particularly conservative in that it helps findings events that are truly firm-specific only, therefore if anything erring on the side of under-estimating cross-firm spillovers. In particular, our two-step identification procedure relies on (i) the identification of large idiosyncratic movements in daily equity returns and (ii) narrative evidence confirming a firm-specific origin of these events.

For the first part of our identification scheme, we estimate the residual component of firms' equity returns which cannot be explained by common market movements, both at a global and national level. We are careful in controlling for common market developments to only identify events that can be safely labelled as firm-specific, namely influencing only one individual firm at the time. In the second part, we add narrative evidence on the origins of the events identified in the first step in order to safely disentangle events which are predominantly driven by common market factors from firm-specific news such as earnings releases, mergers and acquisitions, changes in the firm top management, scandals and announcement of judicial investigations, and so forth.

Armed with these firm-specific events, we analyse their short-term effects for the firms' own market valuation and spill-overs to other firms in the same sector using local projections. We find that idiosyncratic shocks spawn large effects on the firms' own equity prices, CDS spread and the expected default probability, while contagion across the firms in the sector is generally small. Notably, our results also do not show any prominent differences in the spill-over effects for banks and car companies, different from what could be expected based on the idea that the banking sector is strongly leveraged and inter-connected. In terms of economic significance, a typical negative idiosyncratic shock to banks results in one-time fall in the bank's equity price by 10%, increases its CDS spread by 9 basis points and increases its one-year default probability by 0.05%. The effects of an idiosyncratic shock to a car company are very similar. A negative idiosyncratic shock reduces its equity price by 11%, increases its CDS spread by 8 basis points and increases its default probability in one year time by 0.03%. While we do not find any evidence that certain characteristics of the firms exacerbate the short-term effects of an idiosyncratic shock, we do find that such shocks have medium-term implications for the firms' liquidity and leverage ratios, and price-to-book value. In other words, the firm-specific effects

are persistent and important, at least for the firms themselves.

Furthermore, we find mixed results for the granularity our firm-specific shocks as they found to have a significant effect on the equity price index of the sector, while the change in in the VIX and the Dollar-Euro exchange rate is only significant in response to a *negative* idiosyncratic shock.

While we are confident that our approach has neatly identified firm-specific shocks in two key (and very different) sectors of the economy, further research on the granularity of the shocks for global financial and macroeconomic variables is paramount. Ideally, our database may serve as an *instrument* for exogenous changes in financial market conditions, as well as to investigate, at least for the events related to global banks, the hypothesis that their capacity to leverage plays a fundamental role in shaping the global financial cycle (Bruno and Shin (2015)) and exchange rate developments (Gabaix and Maggiori (2015)).

References

- Acemoglu, D., Ozdaglar, A., Tahbaz-Salehi, A., 2015. Systemic Risk and Stability in Financial Networks. *American Economic Review* 105 (2), 564–608.
- Acharya, V. V., Pedersen, L. H., Philippon, T., Richardson, M., 2010. Measuring systemic risk. WP 10-02, Federal Reserve Bank of Cleveland.
- Acharya, V. V., Yorulmazer, T., 2008. Information Contagion and Bank Herding. *Journal of Money, Credit and Banking* 40 (1), 215–231.
- Adrian, T., Brunnermeier, M. K., 2016. CoVaR. *American Economic Review* 106 (7), 1705–1741.
- Allen, F., Babus, A., 2009. Networks in finance. In: Kleindorfer, P. R., Wind, Y. J. (Eds.), *The Network Challenge: Strategy, Profit, and Risk in an Interlinked World*. Wharton School Publishing: New Jersey, pp. 367–382.
- Allen, F., Babus, A., Carletti, E., 2012. Asset commonality, debt maturity and systemic risk. *Journal of Financial Economics* 104 (3), 519–534.
- Allen, F., Gale, D., 2000. Financial Contagion. *Journal of Political Economy* 108 (1), 1–33.
- Anton, M., Polk, C., 2014. Connected stocks. *Journal of Finance* 69 (3), 1099–1127.
URL <https://EconPapers.repec.org/RePEc:bla:jfinan:v:69:y:2014:i:3:p:1099-1127>
- Battiston, S., Delli Gatti, D., Gallegati, M., Greenwald, B., Stiglitz, J. E., 2012. Default cascades: When does risk diversification increase stability? *Journal of Financial Stability* 8 (3), 138–149.
- Ben-David, I., Franzoni, F., Moussawi, R., Sedunov, J., 2016. The Granular Nature of Large Institutional Investors. NBER Working Papers 22247, National Bureau of Economic Research.
- Benoit, S., Colletaz, G., Hurlin, C., Pérignon, C., 2013. A Theoretical and Empirical Comparison of Systemic Risk Measures. HEC Paris Research Paper No. FIN-2014-1030.
- Bisias, D., Flood, M., Lo, A. W., Valavanis, S., 2012. A Survey of Systemic Risk Analytics. *Annual Review of Financial Economics* 4 (1), 255–296.

- Bremus, F., Buch, C. M., Russ, K. N., Schnitzer, M., 2018. Big Banks and Macroeconomic Outcomes: Theory and Cross-Country Evidence of Granularity. *Journal of Money, Credit and Banking* 50 (8), 1785–1825.
- Bruno, V., Shin, H. S., 2015. Cross-border banking and global liquidity. *Review of Economic Studies* 82 (2), 535–564.
- Caballero, R. J., Simsek, A., 2013. Fire Sales in a Model of Complexity. *Journal of Finance* 68 (6), 2549–2587.
- Cetorelli, N., Goldberg, L. S., 2011. Global Banks and International Shock Transmission: Evidence from the Crisis. *IMF Economic Review* 59 (1), 41–76.
- Chan-Lau, J. A., Mitra, S., Ong, L. L., 2012. Identifying Contagion Risk in the International Banking System: An Extreme Value Theory Approach. *International Journal of Finance & Economics* 17 (4), 390–406.
- Chinazzi, M., Fagiolo, G., Reyes, J. A., Schiavo, S., 2013. Post-mortem examination of the international financial network. *Journal of Economic Dynamics and Control* 37 (8), 1692 – 1713.
- Dasgupta, A., 2004. Financial Contagion through Capital Connections: A Model of the Origin and Spread of Bank Panics. *Journal of the European Economic Association* 2 (6), 1049–1084.
- De Bandt, O., Hartmann, P., Peydró, J. L., 2012. Systemic Risk in Banking: An Update. In: Berger, A. N., Molyneux, P., Wilson, J. O. S. (Eds.), *The Oxford Handbook of Banking*, 1st Edition.
- Di Giovanni, J., Levchenko, A. A., Mejean, I., 2014. Firms, Destinations, and Aggregate Fluctuations. *Econometrica* 82 (4), 1303–1340.
- Eaton, J., Kortum, S. S., Sotelo, S., 2016. International Trade: Linking Micro and Macro. NBER Working Papers 17864, National Bureau of Economic Research.
- Elliott, M., Golub, B., Jackson, M. O., 2014. Financial networks and contagion. *American Economic Review* 104 (10), 3115–3153.
- Gabaix, X., 2011. The Granular Origins of Aggregate Fluctuations. *Econometrica* 79 (3), 733–772.

- Gabaix, X., Maggiori, M., 2015. International Liquidity and Exchange Rate Dynamics. *The Quarterly Journal of Economics* 130 (3), 1369–1420.
- Georg, C.-P., 2013. The effect of the interbank network structure on contagion and common shocks. *Journal of Banking and Finance* 37 (7), 2216–2228.
- Glasserman, P., Peyton Young, H., 2015. How likely is contagion in financial networks? *Journal of Banking and Finance* 50, 383–399.
- Gropp, R. E., Duca, M. L., Vesala, J., 2009. Cross-border bank contagion in Europe. *International Journal of Central Banking*, March 2009 5 (1), 97–138.
- Helwege, J., Zhang, G., 2016. Financial Firm Bankruptcy and Contagion. *Review of Finance* 20 (4), 1321–1362.
- Huang, X., Zhou, H., Zhu, H., 2012. Systemic Risk Contributions. *Journal of Financial Services Research* 42 (1), 55–83.
- Jorion, P., Zhang, G., 2009. Credit Contagion from Counterparty Risk. *Journal of Finance* 64 (5), 2053–2087.
- Mink, M., de Haan, J., 2014. Spillovers from Systemic Bank Defaults. CESifo Working Paper Series 4792, CESifo Group Munich.
- Minoiu, C., Reyes, J. A., 2011. A network analysis of global banking: 1978-2009. IMF Working Papers WP/11/74.
- Shleifer, A., Vishny, R., 2011. Fire Sales in Finance and Macroeconomics. *Journal of Economic Perspectives* 25 (1), 29–48.
- Upper, C., 2011. Simulation methods to assess the danger of contagion in interbank markets. *Journal of Financial Stability* 7 (3), 111 – 125.

Table A.1: List of events for carmakers

N	Carmaker	Date	Sign of episode	Change in Stock Price	Brief Description
Type of shock: (i) Earnings					
1	BMW	19/03/2014	+	6.07%	Report of 2014 profit forecast
2	Daimler	15/09/2006	-	-5.77%	Profit warning for 2016
3	Fiat Chrysler	07/05/2014	-	-11.69%	Presentation of Fiat's five-year turnaround plan
4	Fiat Chrysler	07/02/2019	-	-12.21%	Announcement of full-year 2019 outlook
5	Ford	21/04/2004	+	10.18%	Report of first-quarter results for 2004
6	Ford	28/01/2011	-	-13.41%	Report of fourth-quarter results
7	Ford	29/06/2012	-	-4.96%	Report of second-quarter results and worsening outlook
8	Ford	31/10/2012	+	7.72%	Report of third-quarter results
9	Ford	18/12/2013	-	-6.29%	Warning for 2015 profit targets
10	Ford	29/09/2014	-	-7.47%	Profit warning for 2014
11	Ford	28/07/2016	-	-8.16%	Report of second-quarter results and outlook
12	Ford	17/01/2018	-	-7.02%	Profit warning for 2018
13	Ford	26/04/2019	+	10.74%	Announcement of full-year 2019 outlook
14	Ford	25/07/2019	-	-7.45%	Report of second-quarter 2019 results
15	Honda	29/10/2002	-	-13.44%	Report of cut in full-year profit forecast
16	Honda	03/08/2015	+	8.77%	Report of second-quarter results
17	Nissan	05/02/2007	-	-8.35%	Report of full-year profit estimate
18	Nissan	04/11/2008	-	-10.55%	Announcement of profit forecast for the year to March 2009
19	Nissan	05/11/2013	-	-10.41%	Announcement of cut in full-year profit forecast
20	Peugeot	27/07/2004	+	6.27%	Announcement of potentially raising full-year earnings forecast for 2004
21	Peugeot	26/07/2006	-	-10.11%	Profit warning for second-half of 2006
22	Peugeot	24/07/2018	+	14.88%	Report of first-half of 2018 results
23	Renault	25/04/2006	+	7.10%	Report of first-quarter results
24	Renault	12/02/2015	+	11.54%	Report of 2014 full-year results
25	Renault	30/07/2015	-	-7.99%	Report of first-half year results for 2015
26	Suzuki	12/05/2005	-	-7.39%	Announcement of earnings forecast

27	Suzuki	04/08/2017	+	8.70%	Report of first-quarter results
28	Suzuki	11/05/2018	+	8.96%	Report of results for last fiscal year
29	Suzuki	03/08/2018	+	8.55%	Announcement of second-quarter results
30	Toyota	09/05/2018	+	3.76%	Report of fiscal fourth-quarter results
31	VW	10/02/2006	+	7.92%	Announcement of 2005 results and outlook for 2006
32	VW	20/02/2007	+	7.74%	Announcement of full-year 2006 results
33	VW	26/04/2012	+	7.83%	Report of first-quarter results
Type of shock: (ii) Investment					
34	GM	31/05/2018	+	12.87%	SoftBank Vision Fund to invest \$2.3bn in GM's Cruise self-driving unit
35	Honda	02/11/2017	+	5.20%	Announcement of profit forecast upgrade and share buyback
36	Nissan	29/10/2007	+	14.15%	Announcement of joint venture with Indian truckmaker Ashok Leyland
37	Suzuki	27/01/2016	+	11.35%	Nikkei business daily reports possible partnership between Suzuki and Toyota
38	Toyota	16/01/2001	+	12.78%	Announcement of share buyback plan
Type of shock: (iii) M&A					
39	Daimler	14/02/2007	+	7.27%	Restructuring plan: Daimler open to Chrysler sell-off
40	Fiat Chrysler	02/01/2014	+	16.40%	Announcement of agreement to buy remaining 41.5% of Chrysler
41	Fiat Chrysler	29/10/2014	+	12.78%	IPO announcement: Spin-off of Ferrari
42	Renault	27/05/2019	+	12.09%	Fiat Chrysler proposes €33bn merger with Renault
43	VW	18/09/2008	+	25.42%	Porsche acquires another 5% of VW's shares
44	VW	27/10/2008	+	123.73%	Announcement by Porsche to control 74% of VW's voting shares
Type of shock: (iv) Operations					
45	Daimler	28/07/2005	+	9.23%	Resignation of CEO Jürgen Schrempp
46	Fiat Chrysler	12/01/2017	-	-16.14%	Accusations of diesel-emissions cheating by US environmental regulators
47	Fiat Chrysler	25/07/2018	-	-15.50%	Death of CEO Sergio Marchionne, resignation of Fiat Chrysler Europe and report of second-quarter results
48	Ford	26/07/2018	-	-5.99%	Potential \$11bn restructuring charge and cut in earnings guidance due to tariffs
49	Nissan	09/07/2018	-	-4.56%	Nissan admitting to have falsified exhaust emission and fuel economy data
50	Renault	14/01/2016	-	-10.28%	Raid of Renault's offices by French investigators
51	VW	06/10/2004	+	7.19%	Appointment of Wolfgang Bernhard to the VW board
52	VW	21/09/2015	-	-16.55%	Diesel emissions scandal: Announcement of legal provisions to cover the costs of the scandal

Notes: Events are obtained on the basis of a two-step procedure: (i) taking the 7-standard deviation outliers in the standardized residuals of Equation 1, presupposing that only one firm can have an episode of the same sign on any day and the change in the share price needs to be consistent with the sign of the episode and (ii) using narrative evidence confirming the idiosyncrasy of the shock.

Table A.2: List of events for the banking sector

N	Bank	Date	Sign of episode	Change in Stock Price	Brief Description
Type of shock: (i) Earnings					
1	Barclays	07/08/2003	+	9.41%	Report of first-half of 2003 results
2	Barclays	26/01/2009	+	73.23%	Open letter to investors
3	Barclays	11/02/2014	-	-3.75%	Report of fourth-quarter 2013 results
4	Barclays	26/10/2017	-	-7.41%	Report of third-quarter results
5	BNY	16/07/2001	-	-12.96%	Report of second-quarter 2001 results
6	BNY	18/12/2002	-	-15.51%	Report of fourth-quarter earnings forecast
7	BNY	20/07/2005	+	5.08%	Report of quarterly results
8	BNY Mellon	19/04/2018	+	5.70%	Report of first-quarter 2018 results
9	BNY Mellon	17/04/2019	-	-9.52%	Report of first-quarter 2019 results
10	Crédit Agricole	18/11/2004	-	-6.04%	Report of third-quarter results
11	Crédit Agricole	06/11/2014	-	-5.79%	Report of third-quarter results
12	Crédit Agricole	05/11/2015	-	-8.28%	Report of third-quarter results
13	Credit Suisse	15/02/2006	-	-7.50%	Report of fourth-quarter results
14	Credit Suisse	15/02/2007	+	3.50%	Report of fourth-quarter profits and change of chief executive
15	Credit Suisse	04/02/2016	-	-10.89%	Report of 2015 results
16	Credit Suisse	25/04/2018	+	3.55%	Report of first-quarter results
17	Deutsche Bank	27/04/2015	-	-4.83%	Announcement of €3.5bn cost-cutting plan and scale-back of target for profitability
18	Deutsche Bank	29/10/2015	-	-7.72%	Announcement of plan to cut 9,000 jobs and exit 10 countries
19	Deutsche Bank	21/01/2016	-	-3.97%	Report of expected loss for 2015
20	HSBC	01/03/2010	-	-5.23%	Report of full-year 2009 results
21	ING	09/11/2006	-	-4.78%	Report of third-quarter results
22	ING	17/10/2008	-	-27.48%	Warning release on quarterly loss and possible need for a government-backed recapitalisation scheme
23	ING	04/02/2016	+	8.88%	Report of fourth-quarter 2015 results
24	JP Morgan	11/05/2012	-	-9.28%	Announcement of \$2bn trading loss on derivatives
25	Natixis	05/08/2011	+	10.95%	Upgrade to "outperform" at Cheuvreux

26	Natixis	19/12/2018	-	-6.33%	Report of fourth-quarter results
27	Royal Bank of Scotland	19/01/2009	-	-66.57%	Announcement of the biggest loss in Britain's corporate history (£28bn)
28	Royal Bank of Scotland	27/02/2014	-	-7.74%	Report of full-year 2013 results
29	Royal Bank of Scotland	25/07/2014	+	10.77%	Report of second-quarter results
30	Royal Bank of Scotland	26/02/2016	-	-7.13%	Report of full-year 2015 results
31	Royal Bank of Canada	25/02/2005	+	9.10%	Report of first-quarter results
32	Société Générale	01/08/2013	+	10.38%	Report of second-quarter results
33	Société Générale	05/08/2015	+	7.90%	Presentation of capital plan and second-quarter results
34	Société Générale	04/05/2018	-	-5.17%	Report of first-quarter 2018 results
35	Standard Chartered	02/08/2000	-	-10.32%	Announcement to cut 6,000 jobs with report of first-quarter results
36	Standard Chartered	19/02/2003	+	6.87%	Report of 2002 results
37	Standard Chartered	08/08/2005	+	7.64%	Report of second-quarter results
38	Standard Chartered	04/12/2013	-	-6.46%	Profit warning for 2014
39	Standard Chartered	28/10/2014	-	-8.82%	Report of third-quarter results
40	Standard Chartered	01/11/2017	-	-6.05%	Report of third-quarter results
41	State Street	21/03/2003	-	-11.40%	Report of cut in earnings estimate for 2003
42	State Street	13/07/2004	-	-9.21%	Warning for revenue growth in second-half of 2004
43	State Street	19/04/2005	+	8.47%	Report of first-quarter results
44	State Street	20/01/2009	-	-59.04%	Report of fourth-quarter results
45	State Street	18/01/2012	-	-6.55%	Report of full-year and fourth-quarter 2011 results
46	State Street	18/01/2013	+	5.92%	Report of fourth-quarter results
47	State Street	23/01/2015	-	-6.08%	Report of third-quarter results
48	State Street	27/07/2016	+	9.31%	Report of second-quarter results
49	State Street	19/10/2018	-	-8.53%	Report of third-quarter results
50	UBS	31/10/2006	-	-5.05%	Report of third-quarter results
51	UBS	27/07/2010	+	11.21%	Report of second-quarter profits
52	UBS	28/10/2014	+	5.77%	Report of third-quarter results

53	UBS	05/05/2015	+	3.78%	Report of first-quarter results
Type of shock: (ii) Investment					
54	BNY Mellon	18/01/2018	-	-4.39%	Announcement of plans to use tax savings on wages and investment
55	Morgan Stanley	13/10/2008	+	86.98%	Announcement of investment by Mitsubishi UFJ Financial Group
56	Royal Bank of Scotland	05/05/2004	-	-5.63%	Announcement of sale of £2.75bn in new shares
57	Santander	09/01/2015	-	-14.09%	Issuance of €7.5bn in new shares
58	State Street	20/07/2018	-	-7.41%	Announcement of plans to suspend \$950m in share buybacks
Type of shock: (iii) M&A					
59	Bank of America	27/10/2003	-	-10.13%	Announcement of merger with FleetBoston Financial Corp
60	Barclays	01/03/2016	-	-8.11%	Announcement of restructuring along with report of full-year 2015 profits
61	BNY	04/12/2006	+	12.04%	Announcement of M&A BNY and Mellon Financial
62	Crédit Agricole	04/08/2015	-	-10.17%	Crédit Agricole reports problems with the implementation of its reorganisation plan
63	Crédit Agricole	17/02/2016	+	13.91%	Announcement of agreement to simplify the group's structure along with report of fourth-quarter 2015 results
64	ING	26/10/2009	-	-18.00%	Break-up of ING
65	Natixis	18/02/2013	+	22.47%	Announcement of restructuring
66	State Street	05/02/2007	-	-6.51%	Announcement to buy Investors Financial Services for \$4.5bn in stock
67	State Street	17/07/2012	-	-6.37%	Announcement to buy Goldman hedge fund arm and report of second-quarter results
68	Sumitomo	11/08/2005	+	6.56%	Announcement of tender offer to buy more shares in NIF Ventures
Type of shock: (iv) Operations					
69	Bank of America	08/08/2011	-	-20.32%	AIG files \$10bn lawsuit against Bank of America over the quality of mortgages
70	Barclays	28/06/2012	-	-15.53%	Libor scandal: Barclays fined a record £290m
71	BNP Paribas	02/07/2002	-	-9.67%	Le Monde reports on BNP being among Vivendi's main lenders whose credit rating was cut to junk by Moody's Investors Services
72	Citigroup	23/07/2002	-	-15.73%	Unveiling of JP Morgan's and Citigroup's involvement in Enron Corp's finances
73	Goldman Sachs	16/04/2010	-	-12.79%	US authorities accuse Goldman of subprime fraud
74	HSBC	21/02/2017	-	-6.54%	Announcement of annual 2016 profits and investigation for failings around its money-laundering controls
75	JP Morgan	23/07/2002	-	-18.11%	Unveiling of JP Morgan's and Citigroup's involvement in Enron Corp's finances
76	Natixis	20/06/2019	-	-11.76%	Unveiling of H2O Asset Management holding illiquid bonds

77	Santander	30/04/2013	-	-1.15%	Resignation of Santander chief Alfredo Sáenz
78	Société Générale	24/01/2008	-	-4.14%	Société Générale revealed a €5bn fraud by rogue trader Jérôme Kerviel
79	Standard Chartered	07/08/2012	-	-16.43%	DFS report: Allegation of hiding \$250bn of transactions with the Iranian government.
80	UBS	15/09/2011	-	-10.80%	UBS rogue trader scandal
81	UBS	29/10/2013	-	-7.72%	Libor scandal: Fines and legal provisions
82	UBS	15/01/2015	-	-11.74%	SEC Charges UBS \$14m over dark pool disclosures

Notes: Events are obtained on the basis of a two-step procedure: (i) taking the 7-standard deviation outliers in the standardized residuals of Equation 1, presupposing that only one firm can have an episode of the same sign on any day and the change in the share price needs to be consistent with the sign of the episode and (ii) using narrative evidence confirming the idiosyncrasy of the shock.

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