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Non-financial corporations and systemic risk

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ABSTRACT

We investigate the systemic importance of U.S. non-financial corporations and analyse the firm-specific characteristics that identify systemically important non-financial firms. We compute two firm-specific measures of systemic risk for 1145 non-financial corporations and confirm that these firms are both vulnerable to systemic shocks and contribute to system-wide risk, though firms that are high in one dimension of risk are not necessarily high in the other. Systemic risk measures exhibit substantial variation across firms and over time. The firm's beta, value-at-risk, size, debt and trade credit are related to both dimensions of systemic risk, while a range of other firm characteristics are associated with systemic risk in at least one direction. The differences between the dimensions of risk and their associated characteristics underline the importance of analysing both measures of risk.

1. Introduction

Systemic risk and the systemic importance of financial institutions was propelled to the forefront of financial research and debate by the global financial crisis of 2007–09 and later by the Eurozone sovereign debt crisis. Bank failures across many developed countries and the impairment of debt and asset-backed securities markets brought the issue of systemic risk, its measurement and how to combat its threat to global attention. Given that the crisis which precipitated the turmoil originated within the banking sector and associated credit derivative markets (see Brunnermeier, 2009 among others), much of the research on systemic risk has focussed on banks and other non-banking financial institutions. Some papers, e.g. Billio et al. (2012), take a narrow view of the system and limit their focus to the financial sector. However, it is argued by Acharya et al. (2012b) that any definition of systemic risk must incorporate the real economy effects of such a shock. They also stress the importance of the connectedness of the system in measuring systemic risk. Even if firms are individually in good financial health, pervasive linkages across the industry can potentially propagate adverse shocks throughout the system, resulting in widespread disruption and possibly a systemic crisis. Even though non-financial corporations (NFCs) are not strictly part of the financial system, they are inextricably linked to financial institutions through their financing and investment activities. Furthermore, NFCs have important intra-industry linkages through trade credit, supply and production chains, making it difficult to diversify financial exposure to these non-financial firms. Therefore, our goal is to assess the systemic importance of NFCs, both in terms of their contribution to this risk and their vulnerability to it. For a sample of S&P 1500 listed non-financial firms, we compute two measures of systemic risk and relate these to a wide range of firm-level characteristics in an effort to paint a picture of what a systemically important non-financial firm looks like.

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There are many reasons to believe that adverse shocks experienced by these non-financial firms will have repercussions for the financial system and the wider real economy, thus making such firms potentially systemically important. Firstly, in a report on global financial stability, the International Monetary Fund (2019) warn of the imminent threat to the financial system and global economy from 'corporate debt vulnerability'. With corporate indebtedness at record levels, they warn that a shock of half the magnitude of the 2007–08 crisis, would leave about 40% (approximately $19 trillion) of corporate debt at risk across the seven largest economies. This growth in debt financing has been largely due to the low cost of debt and has been accompanied by a declining quality of debt to exacerbate the economic threat (see Celik et al., 2020). Secondly, there is an existing literature on the connections of banks and the real economy. Berger et al. (2020) provides an overview of this literature which establishes the impact of banks on NFCs. Thirdly, from the financial contagion literature, we know that NFCs can play a key role in the transmission of shocks. Korinek et al. (2010) shows how a shock originating in the banking sector can lead to contagion between two NFCs, which were previously unrelated, accentuating the negative effect of the original disturbance. Likewise, network models, such as Acemoglu et al. (2015), show large (either in magnitude or in number) shocks to NFCs can cause fragility in the financial system. Thirdly, empirical evidence that NFCs can propagate an adverse shock to other sectors is provided by Dungey and Gajurel (2015) and Dungey et al. (2020) among others, with strong evidence of bi-directional contagion between the financial and non-financial sectors, in both the U.S. and Eurozone markets.

Measuring systemic risk is a major challenge but a consensus has emerged that all measures should have a time dimension to capture the build-up of systemic risk and a cross-sectional dimension to assess its interconnectedness at a point in time (IMF-FSB-BIS, 2016). The complex nature and dimensionality of systems would suggest that measures of systemic risk require huge volumes of data from the constituent entities of the system and technologies capable of tracking a myriad of bilateral relationships. In this sense, the tedious and painstaking stress tests of financial institutions are likely to produce the most accurate assessment. The downside of this approach is that they are time consuming and repeated infrequently at relatively long horizons. An alternative approach is to use market price data to extract systemic risk measures that are timely and relatively easy to compute. The marginal expected shortfall (MES) of Acharya et al. (2017), the SRISK of Brownlees and Engle (2017), the Delta CoVaR (ΔCoVaR) of Adrian and Brunnermeier (2016) and the Granger-causality approach of Billio et al. (2012) can all be computed from equity prices.[1] Hence these systemic risk measures can be calculated rapidly and updated regularly for any stock market-listed firm.

Using variants of these measures, a voluminous literature has emerged on the systemic importance of financial institutions and the characteristics associated with highly systemic financials. The real-time detection of institutions that are either a threat to, or under threat from, the system is important for regulators challenged with managing crises but equally, identifying the firm-level characteristics of these firms is crucial in forming policy to build resilience in the financial system.[2] Likewise investors can use this information to design investment strategies to hedge against market downturns. Firm size (usually measured as market capitalisation or total assets) is the predominant characteristic associated with systemic risk among financial institutions (see Tarashev et al., 2010; Pais and Stork, 2013; and Laeven et al., 2016 among others). Most studies attribute this relationship to the 'too-big-to-fail' theory, which expects large financial institutions to be 'bailed out' by government rather than allowing them to fail, as it would be too damaging to the system as a whole. Interestingly, firm size has little effect on the risk of individual banks but is important at the system level. Other key determinants of systemic risk for banks is the level of undercapitalisation (Laeven et al., 2016), debt and market-to-book value (Calluzzo and Dong, 2015), the level of interconnectedness with the rest of the financial system (Bostandzic and Weiß, 2018) and corporate governance (Iqbal et al., 2015; and Anginer et al., 2018). Interestingly, better governed firms are generally found to be more systemically risky due to engaging in higher risk activities, again with the expectation of being bailed out if these strategies go wrong.

Despite the sizable literature on financial institutions, relatively few studies have focussed on the systemic risk of non-financial institutions. There are some notable exceptions. Anginer et al. (2018) use a sample of U.S. NFCs as a benchmark against which to compare financial institutions and show that NFCs are systemically risky. Similarly, Dungey et al. (2018) develop an index of systemic importance and show that non-financial firms are consistently among the most systemically important firms, but they stop short of analysing the characteristics of high systemic risk firms. Outside of the U.S., Poledna et al. (2018) analyse a network of Austrian firms and conclude that NFCs are systemically important. They attribute only 29% of total systemic risk to interbank linkages with the remainder emanating from bank-NFC and inter-NFC relationships. Van Cauwenberge et al. (2019) analyse both financial and non-financial Dutch companies and find that NFCs rank among the most systemic firms. They find that size, debt, idiosyncratic risk and the degree of internationalisation are all associated with the systemic risk of Dutch NFCs.

Our research question is related to the aforementioned papers but differs in several important ways. Firstly, we focus on U.S. non-financial firms, arguably the most important corporate market, over a longer time period than other studies. In particular, we analyse a sample of 1145 non-financial S&P 1500-listed firms from 2005 to 2018. Secondly, we study the systemic risk of these NFCs both in terms of their contribution to, and their vulnerability to, system-wide downturns. We compute two systemic risk measures, MES and ΔCoVaR – discussed in greater detail in the next section – to capture this potential bidirectional transmission of shocks between individual firms and the system. These measures differ in the direction of causality. MES captures the vulnerability of the individual firm

[1] Other measures rely on CDS data, e.g. Huang et al. (2009); interbank market data as in Langfield et al. (2014); and bond data as in De Sola Perea et al. (2019).

[2] Even though our focus here is on firm-specific characteristics here, common risks may also be important and may feed through to the firm-level variables. For example, Matousek et al. (2020) show how economic policy uncertainty can influence the capital shortfall of global financial institutions.

to a system-wide shock, while ΔCoVaR estimates the effects of a firm-specific shock on the wider system.[3] Thirdly, we look for the association between systemic risk and a broader range of firm-level characteristics (which are discussed in Section 3) than employed in other studies to ascertain a more complete understanding of what firm-level characteristics are associated with the systemic risk of NFCs and to assess if these are the same characteristics found, in the existing literature, to predict the systemic risk of financial firms. Fourthly, we employ a relatively new estimation technique that is ideally suited to our analysis as it allows us to distinguish between factors associated with the build-up (time dimension) and factors that capture the interconnectedness (cross-sectional dimension) of systemic risk. Specifically, we estimate a series of 'random effects within between' (REWB) regressions (see Bell and Jones, 2015). In REWB regressions, the cross-sectional (between) and longitudinal (within) relationship between each firm characteristic and systemic risk are estimated simultaneously, allowing us to identify characteristics that are associated with differences in systemic risk *between* firms and those associated with the evolution of systemic risk *within* the firm over time. Most studies of systemic risk employ fixed-effect regressions which only pick up the within-firm effect, and thus implicitly ignore between-firm effects.

Our results reveal a number of interesting findings. Firstly, we confirm that non-financial firms are systemically important with substantial and persistent MES and ΔCoVaR measures. Though usually lower than the corresponding measures for financials, the systemic risk measures of NFCs exhibit strong persistence over time regardless of market conditions. Furthermore, both measures exhibit large variation across firms and over time. Secondly, distinguishing between systemic vulnerability and systemic contribution is important as we find a great deal of heterogeneity in the measures. Firms who rank highly in one risk dimension do not necessarily rank highly in the other. Hence focusing on a single measure of systemic risk would miss vital aspects of the phenomenon and lead to inefficient policy formulation. Thirdly, many more variables are related to NFC systemic risk than those identified in the literature as driving systemic risk among banks and other non-banking financial institutions, reinforcing the need for our analysis. Fourthly, we provide empirical evidence on the warnings of the International Monetary Fund (2019) report regarding the systemic threat of highly indebted corporations. Higher debt ratios are associated with greater vulnerability to a market-wide shock (MES) but lower systemic contribution (ΔCoVaR). This suggests that the allocation of debt to NFCs may already take the systemic risk of firms into account and/or that credit providers are able to hedge these credit risks. Trade credit is also important for understanding systemic risk. This shows that firm linkages that are external to the financial system can also generate systemic risk and have the potential to impact on the wider economy. Interestingly, irrespective of the direction of shock transmission, firms who provide trade credit are always of higher systemic importance than firms who receive it. Fifthly, the remaining firm characteristics associated with high systemic vulnerability are very different from those of firms who contribute to systemic risk. This underlines the need for analysing systemic risk across both dimensions. Similarly, the factors that capture the build-up of systemic risk are largely different from those that capture systemic importance due to cross-sectional interconnectedness, showing that the REWB regressions reveal extra information about systemic risk.

The remainder of this paper is structured as follows. Section 2 details the employed measures of systemic risk, describes their computation and presents these measures for our sample of non-financial firms. Section 3 lists, and provides motivation for, the firm-specific characteristics that we include in our regression analysis. It then proceeds to present some preliminary univariate statistics before outlining our econometric methodology. Section 4 discusses our results, while Section 5 contains our concluding remarks.

2. Measures of systemic risk

The need for up-to-date information on systemic risk has led researchers to develop systemic measures based on publicly-available information, with their timeliness appealing to both policymakers and investors who need to react to unfolding events to minimise the negative repercussions associated with systemic episodes. We compute two of the most popular measures; the marginal expected shortfall (MES) of Acharya et al. (2012b) and Adrian and Brunnermeier' s (2016) ΔCoVaR.[4] We briefly review these measures and describe their computation before presenting the results for our sample of 1145 S&P-listed firms.[5]

2.1. Marginal expected shortfall (MES)

Acharya et al. (2017) define MES as the marginal contribution of firm *j* to the expected shortfall of the financial system, termed the market portfolio, and captures the vulnerability of firm *j* to a system-wide shock. Specifically, the MES of firm *j* is its average stock return for the days in which the market has experienced a systemic (or tail) event. We define such an event as days in which the market return is in the 5% tail of its return distribution. We choose the S&P 500 index as our market portfolio as it closely reflects the performance of the real economy and, for each year of our sample, we compute the firm specific MES as:

$$MES_{j,5\%} = \frac{1}{\#Days_{Mkt\ Return\ is\ in\ its\ 5\%tail}} \sum r_j \tag{1}$$

We use the negative of MES so that firm-level systemic vulnerability is increasing in MES.

[3] Adrian and Brunnermeier (2016) show that the causality of their ΔCoVaR measure can be reversed to capture the effect of a systemic shock on individual firms.

[4] The SRISK measure of Brownlees and Engle (2017) is similar to the MES and often used in the banking literature. Since it incorporates a capital requirement ratio, we exclude it from our analysis of NFCs.

[5] Brunnermeier et al. (2020) provide step-by-step details of the computation of these measures and we follow their approach in this study.

2.2. Delta CoVaR

We estimate a firm's ΔCoVaR (Adrian and Brunnermeier, 2016) to capture the systemic contribution of each firm, i.e. the transmission of a firm-specific shock to the overall system. ΔCoVaR captures the systemic impact of a firm's distress upon the financial system by estimating the change in the financial system's value-at-risk (VaR) that takes place conditional upon a tail event for firm *j*. For consistency with our MES variable, we define a tail event for firm *j* as when it experiences a return that is in its worst 5% of returns for a given period. The VaR of firm *j* is

$$Probability\left(r_j \leq VaR_{j,5\%}\right) = 5\% \tag{2}$$

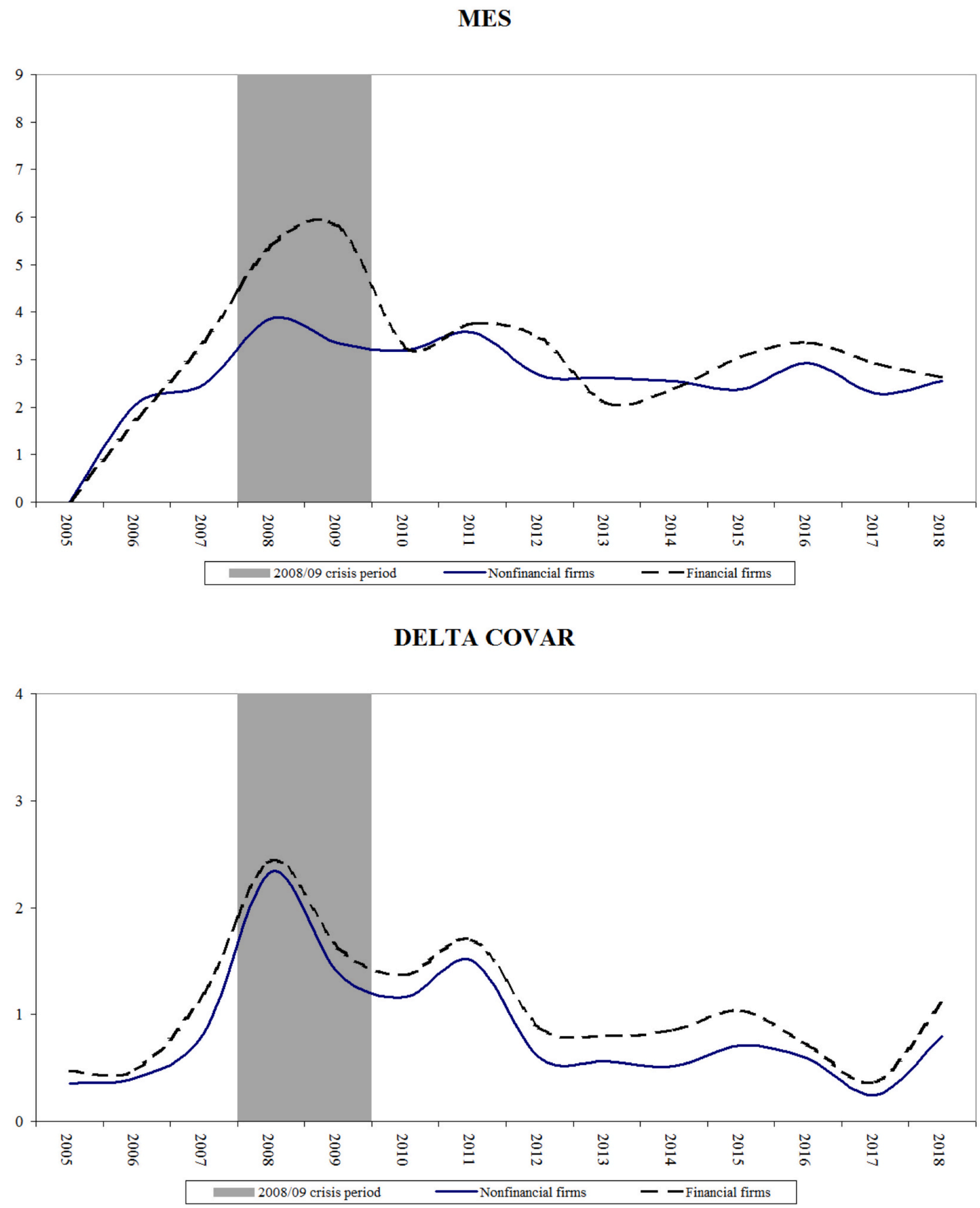

Fig. 1. Systemic risk over time.
This figure presents median annual ΔCoVaR and median annual MES in each year from 2005 to 2018 for nonfinancial firms and financial firms. The global financial crisis period (2008–2009) is shaded in grey. Shaded cells refer to maximum values.

ΔCoVaR relies on two conditional VaR estimates (CoVaR). The financial system's CoVaR when firm *j* experiences a tail event, is defined as follows:

$$Probability\left(r_{fs} \leq CoVaR^{system|j} | r_j = VaR_{j,5\%}\right) = 5\% \tag{3}$$

Here r_{fs} represents the return of the financial system (market) and r_j is the return for firm *j*. Repeating the estimation, but conditioning upon the firm's 50% VaR we estimate the firm's ΔCoVaR as follows:

$$\Delta CoVaR\ \left(R_{fs}|j, 5\%\right) = CoVaR\ \left(R_{fs}|j, 5\%\right) – CoVaR\ \left(R_{fs}|j, 50\%\right) \tag{4}$$

ΔCoVaR is the change in the value-at-risk of the financial system when firm *j* goes from its median return to experiencing a left-tail event. As proposed by Adrian and Brunnermeier (2016), we rely on quantile regression techniques to estimate this measure. Time variation in ΔCoVaR is generated by the inclusion of a number of state variables, and following Adrian and Brunnermeier (2016), we include lagged values of the market return, market volatility (22-day standard deviation of market returns), the change in the 3-month Treasury bill rate, term premium, the TED spread (which is often used to capture market liquidity), and the credit spread in our specification. We use annual averages of ΔCoVaR in our subsequent analysis of firm characteristics (as in Anginer et al., 2018). As with MES, and for ease of interpretation, we use the negative of ΔCoVaR so that larger values implies higher contribution to systemic risk.

2.3. *Systemic importance of U.S. non-financial firms*

As a first step in our analysis, we compute and analyse the MES and ΔCoVaR measures for each of the 1145 non-financial firms in our sample over the period 2005–2018. Each firm can be allocated to one of eight non-financial sectors according to the Industry Classification Benchmarks (ICB) and some of our results are presented by industry to facilitate a clearer exposition. Fig. 1 plots the median MES (top panel) and ΔCoVaR (lower panel) of all NFCs over time. The corresponding figures for a sample of U.S. financials is included as a benchmark. An interesting pattern emerges. In general, financials score higher than NFCs in both dimensions of systemic risk but the systemic vulnerability and contribution to systemic risk is still significant across non-financial firms. In the early years of our sample, 2005–06, both measures are relatively low implying that systemic risk was not a major threat to individual firms or to the broader economy. This changes quickly and significantly with the onset of the U.S. financial crisis in 2007. MES climbs quickly and steeply, particularly for the financial sector. There is a clear differential in systemic risk between financials and NFCs during the crisis years, but it is noticeable that MES declines much more sharply for the former than for non-financial firms. This suggests that resolution programmes introduced to rescue banks and build resilience in the financial sector enjoyed some success. However, many of these policies initiated by government, though aimed at alleviating distress in the financial sector, often had an implicit assumption that a fully functioning financial system would keep credit flowing to NFCs and thus protect them from the financial shock. Fig. 1 indicates that this knock-on effect was not strong enough to insulate non-financials from the crisis. The prolonged vulnerability of non-financials may be due to the lack of any targeted rescue programmes for NFCs (with the exception of the automobile industry) and further aggravated by a global economic downturn and poor consumer demand in international markets, and Europe in particular. Post crisis, the MES of financials and NFCs move together and show that the systemic vulnerability in both sectors was similar.

ΔCoVaR for the two sectors exhibits higher correlation than MES. For both financials and NFCs, Fig. 1 shows that there is the potential to transmit adverse shocks to the wider system and thus, this risk needs to be managed not only for banks and financial firms but also for non-financials. Our measure of systemic contribution is consistently higher for financials than for NFCs but the difference is relatively small. It grows from negligible values in 2005 to its peak in 2008. Its peak coincides with the collapse of Lehman Brothers and the introduction of TARP and related programmes aimed at strengthening the riskiest banks and decoupling these banks from the wider financial system. Post-crisis, ΔCoVaR declines in 09–10 before jumping back up in 2011 as the Eurozone sovereign debt crisis created increased uncertainty in the global economy. Thereafter, it decreases steadily as markets recovered before increasing once again in 2018 as stock market uncertainty took hold once more due to the U.S. – Chinese trade war and a number of interest rate increases by the Fed.

Table 1 presents some summary statistics at a sectoral level. MES has a higher mean and standard deviation than ΔCoVaR reflecting that market shocks evoke responses of greater magnitude from individual firms than market responses to firm-specific shocks. On average, MES is highest for Energy stocks, with firms in the technology, industrials and basic materials sectors also relatively more vulnerable to a market tail event. This ordering is preserved across the distribution. ΔCoVaR also exhibits great variation across sectors but once more it is stocks from the energy, technology, industrials and basic materials sectors that have the highest average values in this dimension of systemic risk. Kerste et al. (2015) also note the systemic risk of the energy sector. However, looking at the upper percentiles of both distributions, we see that all NFC's have instances of very large systemic risk, both in terms of vulnerability to a market shock and their contribution to systemic risk.

Fig. 2 plots the median level of MES (top panel) and ΔCoVaR (lower panel) for each of our sectors across different sub-periods. For each sector, MES is at its highest during the 2008–09 period and is highest for Financials during this period. Interestingly, this is the only sub-period for which Financials have the highest value of MES. In other sub-periods, sectors such as Energy, Technology and Basic Materials surpass the systemic vulnerability of Financials. Focusing on ΔCoVaR, the values across sectors are much more similar but again, non-financial sectors sometimes exceed financial firms in terms of systemic contribution. Taken as a whole, Fig. 2 tells us that NFCs are systemically important in both dimensions of the risk.

Finally, we address the question if it is the same firms scoring highly in both systemic risk measures. Fig. 3 shows a scatter plot of MES versus ΔCoVaR. For ease of exposition, we divide the time period into sub-periods. If the ranking of firms is the same in both

Table 1
Systemic risk across industry sectors.

MES is systemic risk measure										
	Obs	Firms	Mean	p25	Median	p75	p95	Std. dev	Min	Max
Technology	1780	181	3.02	2.17	2.90	3.81	5.60	1.58	(1.12)	22.48
Telecommunications	401	41	2.61	1.75	2.52	3.41	5.16	1.46	(2.78)	8.29
Health Care	1818	192	2.45	1.67	2.36	3.23	5.18	1.62	(11.83)	13.14
Consumer Discretionary	2602	255	2.70	1.87	2.60	3.49	5.35	1.51	(2.25)	15.94
Consumer Staples	809	71	1.74	1.17	1.73	2.36	3.59	1.09	(3.54)	6.33
Industrials	3037	268	2.87	2.12	2.82	3.66	5.19	1.44	(3.08)	16.07
Basic Materials	768	68	3.03	2.15	2.93	4.05	6.04	1.71	(2.80)	10.94
Energy	732	69	3.23	2.20	3.16	4.25	6.27	1.84	(5.01)	14.37
ΔCoVaR is systemic risk measure										
Technology	1780	181	0.81	0.43	0.66	1.05	1.93	0.55	(0.27)	3.35
Telecommunications	401	41	0.78	0.37	0.61	1.04	2.08	0.60	(0.09)	3.21
Health Care	1818	192	0.68	0.32	0.55	0.88	1.83	0.54	(0.40)	3.76
Consumer Discretionary	2602	255	0.77	0.39	0.62	0.99	1.93	0.55	(0.19)	3.30
Consumer Staples	809	71	0.76	0.35	0.61	1.01	1.96	0.57	(0.23)	3.20
Industrials	3037	268	0.91	0.49	0.74	1.16	2.14	0.60	(0.12)	3.67
Basic Materials	768	68	0.91	0.49	0.73	1.17	2.21	0.62	(0.21)	3.60
Energy	732	69	0.87	0.45	0.67	1.17	2.32	0.62	(0.19)	3.18

This table summaries systemic risk measures across each ICB industry group. Systemic risk is measured using each of marginal expected shortfall (MES) and Delta CoVar (ΔCovar), as indicated. For each risk measure we report the mean, 25th percentile (p25), median, 75th percentile (p75), 95th percentile (p95), the overall standard deviation, minimum and maximum. The risk measures are observed in each year in the period 2005–2018. Note that the summary measures are based on the raw risk measures which have not been winsorized.

dimensions of risk, then we should see firms on or close to a 45-degree line. That is not the case, particularly for the crisis and post-crisis periods. While, the relationship is positive, it is far from a 1:1. Table 2 lists the names of the top (most risky) and bottom (least risky) 10 non-financial firms in terms of their average MES (upper panel) and ΔCoVaR (lower panel) scores across the whole sample. Strikingly, no firms appear in the top 10 of both risk measures, while three firms feature in the bottom 10 (least risky) of both MES and ΔCoVaR. Table 2 also shows the rank of each firm in terms of the other risk measure. It confirms great variation between their MES and ΔCoVaR measures. Likewise, we include the firm Beta (which captures its market risk) and, once again, there is considerable variation. Table 3 presents an equivalent analysis for a sample of well-known firms. Again, the lack of positive correlation between their MES and ΔCoVaR is striking. Some of these household names are ranked high in terms of systemic contribution but low in terms of systemic vulnerability, e.g. Ford, Chevron and Exxon Mobil. Interestingly, Ford is the highest systemic contributor during the crisis years and also ranks highly in the MES score, showing that the decision to extend the TARP programme to the automobile industry was probably necessary. Overall, the firms that are most vulnerable to a systemic crisis tend not to be the same as those who contribute most to such an event. Consequently, it is crucial to analyse systemic risk across both dimensions as focusing on just one measure would overlook important information about risk and produce less effective policies to combat its spread.

A more detailed analysis of Fig. 3 permits the classification of non-financials in terms of systemic risk. Dividing the plots into four quadrants, we see that at one extreme (south-west quadrant), there are firms who score low in both risk measures. These firms are not systemically important, i.e. their shocks do not endanger the system and they show little vulnerability to system-wide shocks. At the other extreme (north-eastern quadrant), there are a group of firms who simultaneously show high vulnerability to a systemic shock and whose own shocks contribute to a broader downturn. These firms have the capacity to propagate shocks across the system, not alone through their own idiosyncratic shocks but by feedback effects with the wider financial system. Firms in the off-diagonal quadrants tend to be high in one dimension of systemic risk and low in the other. While either showing high vulnerability or high contribution to tumultuous episodes, there is little danger of bidirectional feedback effects aggravating the crisis.

3. Data and econometric methodology

Having established that non-financial U.S. firms are of systemic importance, we seek to identify the firm-level characteristics that contribute to this type of risk, following the extant literature on banking and other non-banking financial firms.

3.1. Potential firm-specific drivers of systemic risk

Without a guiding theory as to the factors that may potentially contribute to systemic risk, we identify a set of potentially important variables from the literature on individual risk and beta risk and use regression analysis to determine their importance to systemic

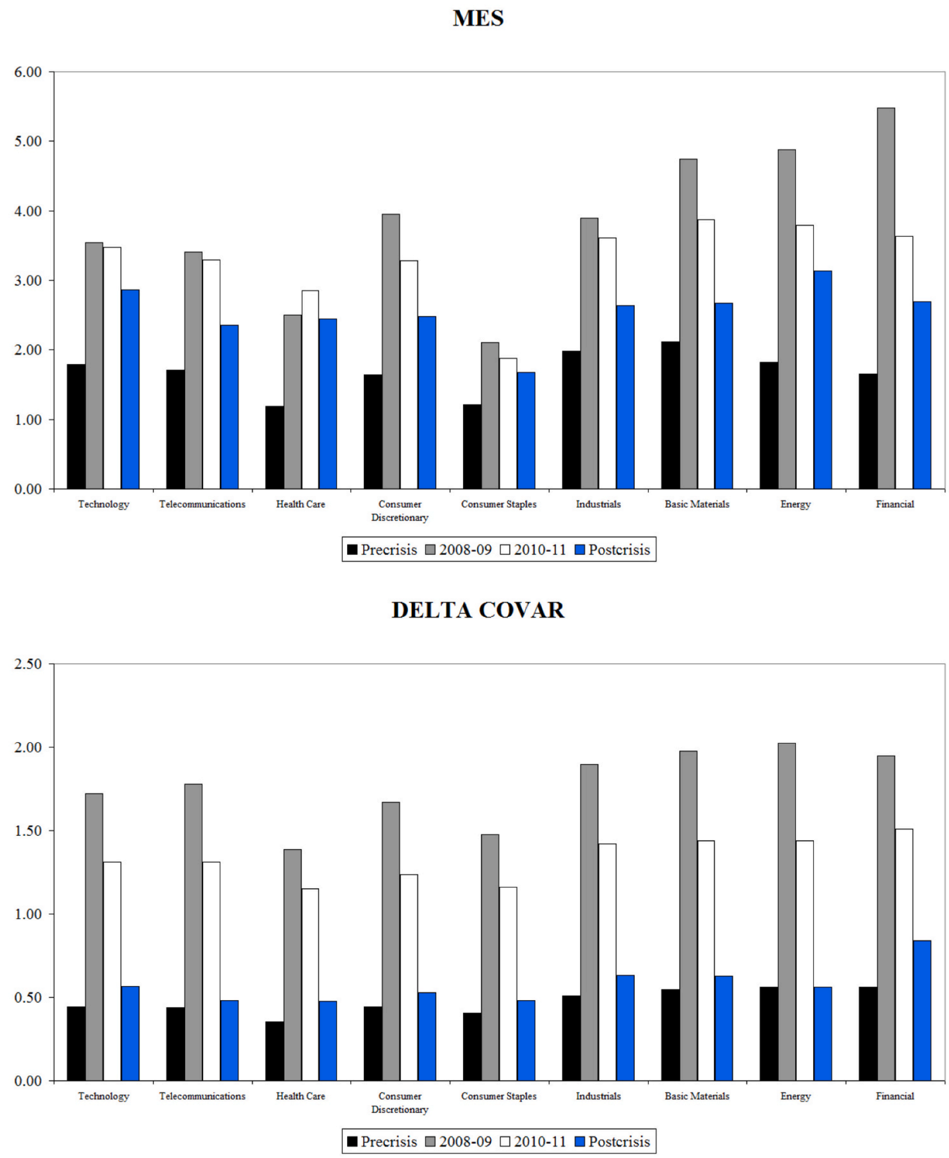

Fig. 2. MES and ΔCoVaR across industry sectors.
Shaded (bold) cells refer to maximum (minimum) values. Median figures presented. Note MES is zero in the pre-crisis period (2005–2007) in all industries.

risk.[6] Beta risk may be relevant since Benoit et al. (2013) describe MES and ΔCoVaR as transformations of beta (or something similar to beta in the case of ΔCoVaR). Table 4 lists and describes the variables used in the study. It also provides some summary statistics and the source of the data. In the remainder of this subsection, we provide a brief motivation on the choice of these variables. We begin with firm-specific measures of risk, namely the firm's beta and its 5% VaR. These measures capture a firm's connectedness to the market and its own tail risk respectively. One of the most direct links between a NFC and the financial system is through its use of debt financing. The International Monetary Fund (2019) report focuses on the threat to global financial stability being posed by the level of corporate indebtedness across the largest economies. Our regressions include a number of debt-related variables to capture this potential relationship, namely the level of debt (measured as total debt to market capitalization) and the maturity structure of debt (long-term financial debt to total financial debt). Other dimensions of a firm's relationship with external markets are captured through external

[6] We bear in mind that studies on the drivers of systemic risk in banks have shown that some characteristics that are risk reducing at the firm level can have the opposite effect (or no effect) at the system-level (see for example, Wagner, 2010; Mayordomo et al., 2014, among others). Notwithstanding, factors that have been shown to influence firm-specific risk and its beta risk seems a reasonable starting point.

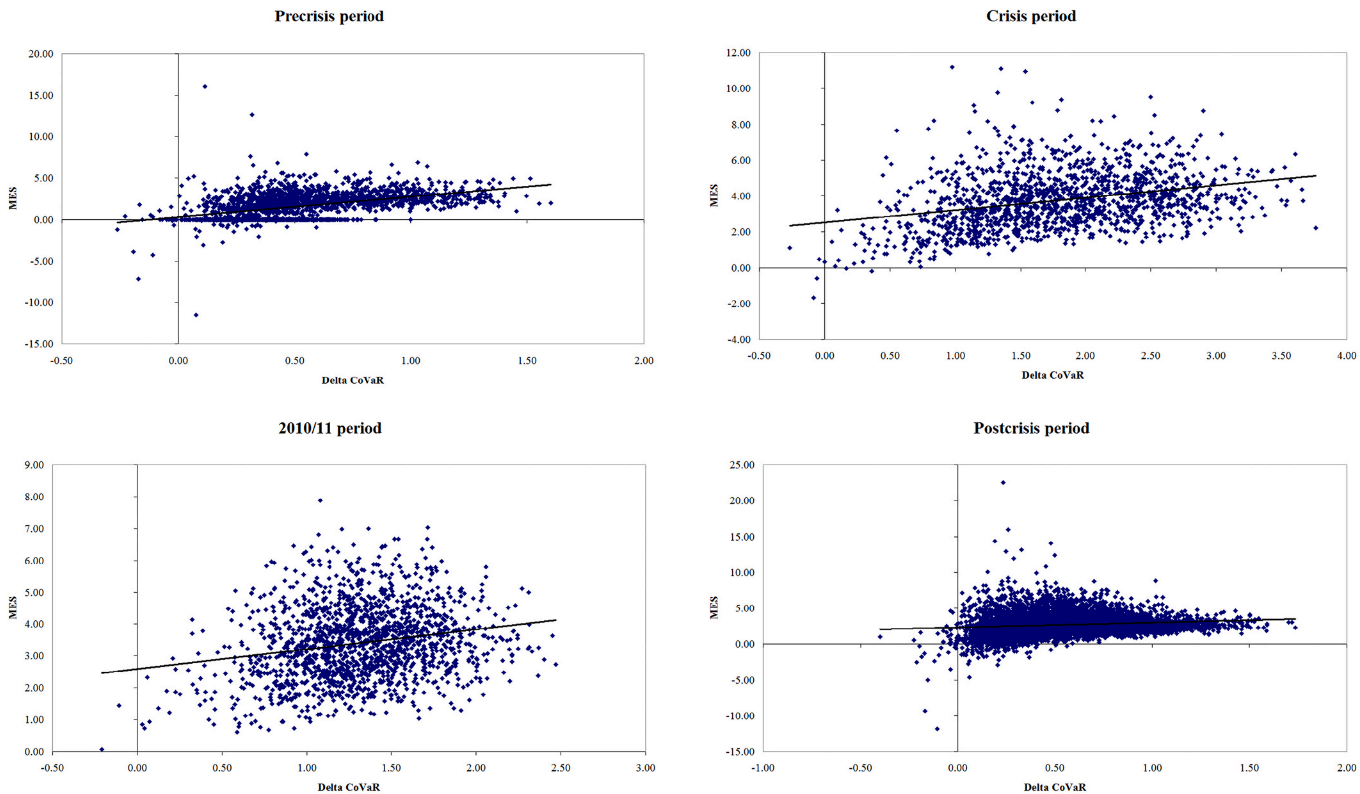

Fig. 3. The relationship between MES and ΔCoVaR.
This figure presents ΔCoVaR-MES scatter plots for the pre-crisis period (2005–2007), the global financial crisis period (2008–2009), the 2010/11 period, and the post-crisis period (2012–2018).

Table 2
Firms with largest and smallest vulnerability (MES) and contribution (ΔCovar) to systemic risk.

Company	Industry	MES	ΔCovar	ΔCovar rank	Beta
MES: Top 10					
Triton International	Industrials	7.73	0.51	849	2.63
Enphase Energy	Energy	6.74	0.30	1107	0.27
New Relic	Technology	6.38	0.51	855	0.96
Box CL.A	Technology	5.95	0.60	678	1.25
Builders Firstsource	Industrials	5.86	0.61	631	2.21
Cara Therapeutics	Health Care	5.57	0.41	1012	3.34
W&T Offshore	Energy	5.45	0.61	636	1.90
Chemours	Basic Materials	5.32	0.56	769	3.10
Dicerna Pharmaceuticals	Health Care	5.23	0.30	1106	2.83
Hubspot	Technology	5.23	0.45	956	2.10
MES: Bottom 10					
Innoviva	Health Care	0.00	0.15	1141	1.46
Vista Outdoor	Consumer Discretionary	0.28	(0.04)	1145	0.77
Ollies Bargain Outlet	Consumer Discretionary	0.30	0.25	1125	0.30
Pacific Basics of Cal.	Health Care	0.69	0.23	1132	2.49
Mimedx Group	Health Care	0.93	0.31	1105	0.85
Campbell Soup	Consumer Staples	1.07	0.70	445	0.39
Lemaitre Vascular	Health Care	1.08	0.20	1138	0.53
Kimberly-Clark	Consumer Staples	1.10	0.85	156	0.36
Kellogg	Consumer Staples	1.17	0.68	493	0.47
Royal Gold	Basic Materials	1.18	0.32	1099	0.44

Company	Industry	ΔCovar	MES	MES rank	Beta
ΔCovar: Top 10					
Robert Half International	Industrials	1.51	3.60	172	1.55
Sysco	Consumer Staples	1.47	2.13	929	1.56
Marriott International	Consumer Discretionary	1.35	3.21	329	1.21
Loral Space	Telecommunications	1.32	2.64	651	1.82
L Brands	Consumer Discretionary	1.30	3.19	334	1.39
SM Energy	Energy	1.20	3.74	136	1.20
Norfolk Southern	Industrials	1.17	2.85	529	0.79
RPM International	Industrials	1.14	2.91	484	1.14
MSC Indl Direct	Industrials	1.14	2.81	550	1.55
Kennametal	Industrials	1.13	3.82	120	1.10
ΔCovar: Bottom 10					
Cryoport	Industrials	0.09	2.86	520	0.46
Innoviva	Health Care	0.15	0.00	1145	1.46
Inovalon Holdings	Health Care	0.22	2.48	735	0.96
Insmed	Health Care	0.11	1.49	1105	0.25
Lemaitre Vascular	Health Care	0.20	1.08	1139	0.53
Sarepta Therapeutics	Health Care	0.16	2.80	557	1.08
Sorrento Therapeutics	Health Care	0.06	3.35	271	1.94
Upland Software	Technology	0.20	2.18	904	0.40
Vista Outdoor	Consumer Discretionary	0.05	0.28	1144	0.77
Vonage Holdings	Telecommunications	0.22	3.38	253	1.41

This tables lists the top-10 (most risky) and bottom-10 (least risky) firms based on their median level of systemic risk calculated over the sample period. Systemic risk is measured using each of marginal expected shortfall (MES) and Delta CoVar (ΔCovar), as indicated.

financial dependence (capital expenditures less net cash flows from operations divided by capital expenditures) and a "size-age" measure of financing constraints (due to Hadlock and Pierce, 2010). Trade credit may also be important as it captures linkages between non-banking lenders and borrowers. Corporate defaults may produce contagious effects through the type of balance-sheet contagion described by Kiyotaki and Moore (2002) and the type of default chain in Das et al. (2007). Trade credit linkages are captured through accounts payable (accounts payable to assets), and accounts receivable (accounts receivables to assets). It is often found that firms with a reliance on external capital and trade credit perform worse during financial crises (see Rajan and Zingales, 1998; Beck et al., 2004; and Love et al., 2007).

As discussed earlier, firm size is consistently found to be a significant determinant of systemic risk in the banking literature with its significance frequently attributed to the 'too-big-to-fail' theory and the expectation of rescue packages being offered to large financial institutions. Without the tacit belief that such a rescue package will be provided to NFCs, it is an interesting empirical question as to whether or not size influences systemic risk in our sample of non-financial firms. We include firm assets as an absolute measure of size and market share (firm sales to total industry sales) as a measure of importance within an industry. Corporate governance is another variable that has been shown to impact on the systemic risk of financial firms. Again, this is often related to the risk-taking behaviour of

Table 3
Systemic risk and beta risk for selected firms.

Name	First year in sample	Industry sector	MES				ΔCovar				Beta	
			Median	Rank	Crisis years median and rank		Median	Rank	Crisis years median and rank		Median	Rank
Abbott Laboratories	2004	Health Care	1.71	1077	1.31	780	0.95	58	1.17	505	0.53	1100
Amazon	2005	Consumer Discretionary	2.61	669	2.75	541	0.53	817	0.64	767	1.21	597
Apple	2004	Technology	2.66	627	2.73	545	0.88	124	1.37	298	1.31	510
AT&T	2004	Telecommunications	1.72	1075	1.87	719	0.88	118	1.48	205	0.63	1054
Boeing	2004	Industrials	2.60	674	3.70	311	1.04	26	1.26	412	1.21	599
Chevron	2004	Energy	2.58	681	2.79	527	1.07	18	2.00	5	0.78	956
Cisco Systems	2004	Telecommunications	2.74	586	3.00	473	0.67	528	1.76	29	1.28	530
Coca-Cola	2004	Consumer Staples	1.39	1121	1.53	757	0.84	173	0.89	693	0.53	1089
Conoco Phillips	2004	Energy	2.63	655	3.04	461	0.79	269	1.74	36	1.04	752
Ebay	2004	Consumer Discretionary	2.60	675	2.76	538	0.68	489	1.46	216	1.48	377
Exxon Mobil	2004	Energy	2.40	778	2.39	609	0.99	42	2.00	6	0.64	1051
Facebook	2012	Technology	3.26	302	–	–	0.54	799	–	–	0.58	1076
FedEx	2004	Industrials	3.09	390	3.67	318	0.93	79	1.76	31	1.04	753
Ford Motor	2004	Consumer Discretionary	2.95	464	5.67	43	0.80	243	2.44	1	1.49	373
General Electric	2004	Industrials	2.55	700	4.07	228	0.83	182	1.52	165	1.19	617
General Mills	2004	Consumer Staples	1.27	1132	0.96	801	0.70	465	1.08	587	0.21	1158
Google	2004	Technology	2.43	763	2.67	559	0.99	37	1.40	265	1.06	732
Home Depot	2004	Consumer Discretionary	2.37	798	2.63	564	0.87	132	1.52	169	0.96	819
Intel	2004	Technology	2.24	881	2.95	484	0.93	69	1.46	211	1.09	705
IBM	2004	Technology	1.89	1028	1.78	727	1.07	19	1.29	379	0.98	817
Johnson & Johnson	2004	Health Care	1.59	1094	1.42	772	0.98	47	1.29	383	0.56	1084
McDonalds	2004	Consumer Discretionary	1.39	1122	1.45	764	0.87	139	1.38	294	0.57	1078
Microsoft	2004	Technology	2.60	672	2.61	570	0.74	368	1.30	377	0.98	797
Netflix	2004	Consumer Discretionary	3.35	267	2.45	598	0.32	1095	0.36	799	1.24	560
Oracle	2004	Technology	2.40	776	2.60	571	1.03	27	1.21	470	1.20	627
Pepsico	2004	Consumer Staples	1.45	1111	1.54	755	0.86	148	1.23	440	0.51	1098
Pfizer	2004	Health Care	1.69	1080	2.08	672	0.92	86	1.15	524	0.72	1002
Procter & Gamble	2004	Consumer Staples	1.25	1134	1.51	758	0.65	576	1.42	248	0.49	1111
Tesla	2010	Consumer Discretionary	3.21	325	–	–	0.38	1041	–	–	0.42	1130
United Airlines	2006	Consumer Discretionary	2.61	662	6.72	17	0.72	401	0.95	658	1.05	740

This tables lists firms median systemic risk and beta for selected firms. Systemic risk is measured using each of marginal expected shortfall (MES) and Delta CoVar, (ΔCovar), as indicated. Crisis years refers to years 2008 and 2009.

large shareholder-friendly banks but, nevertheless, we include it as a potential determinant of NFC systemic risk. We use Refinitiv ESG corporate governance scores to capture the corporate governance scores of each firm.

The financial health of the firm and its ability to meet its short-term obligations also has the potential to impact upon the overall system. We use a range of variables to capture these effects; profitability (operating income to assets), cash holdings (cash to assets), payout variables (binary dummy variables that indicate if a firm pays dividends, repurchases shares or both), growth opportunities (market to book value of assets) and asset tangibility (gross property, plant and equipment to assets).

The lifecycle stage of a firm may also be important in determining its vulnerability or contribution to systemic risk. We include three measures of lifecycle, firm age (using firm incorporation dates), RE/TE (retained equity to total equity), and a lifecycle classification based on the multiclass linear discriminant analysis (MLDA) of Faff et al. (2016). The latter approach allocates firms to one of four lifecycle stages; birth, growth, mature, and shakeout/decline. Chincarini et al. (2016) finds that early stage firms are most vulnerable to market risk (beta risk), while this fragility declines over time. In contrast, well-established, mature firms are expected to contribute most to systemic events.

The degree of international exposure has been shown to influence individual firm risk (Mitton, 2002) and the systemic contribution of Dutch firms (Van Cauwenberge et al., 2019). There are two competing channels for this effect as internationalisation may reduce risk through diversification or increase risk due to exposure to non-domestic shocks. We include foreign sales (foreign sales to total sales) to capture the effects of internationalisation on systemic risk. Product market conditions have also been shown to be an important determinant of individual firm risk (Behrens et al., 2013). We use R&D expenditure (R&D expense to assets), as a proxy for this phenomenon.

Table 4
Variable description and summary statistics.

Measure	Definition	Mean	p25	Median	p95	Standard deviation			Source
						Overall	B-SD	W-SD	
MES	Systemic risk vulnerability of firm	2.74	1.88	2.65	5.38	1.57	0.83	1.36	Datastream and author calculations
ΔCovar	Systemic risk contribution of firm	0.81	0.41	0.66	2.00	0.58	0.22	0.54	
VaR	5% Value at Risk (VaR)	3.62	2.29	3.14	7.53	1.96	1.20	1.61	
Beta	Systematic risk of firm using S&P500 index	1.28	0.81	1.19	2.61	0.72	0.55	0.50	Datastream
Corporate governance	Corporate governance scores	49.21	31.08	49.70	84.14	22.07	18.51	13.61	Refinitiv ESG
Size	Book assets in billions of $US	8.63	0.67	2.02	37.73	20.04	18.04	5.99	Thomson Reuters
Foreign sales	Foreign sales as a % of total sales	0.30	0.00	0.25	0.84	0.29	0.28	0.09	Thomson Reuters
Debt	Total debt to market capitalization	0.30	0.03	0.15	1.11	0.29	0.40	0.29	Thomson Reuters
Debt maturity	Long-term financial debt to total financial debt	0.71	0.58	0.90	1.00	0.47	0.31	0.22	Thomson Reuters
Accounts payable	Accounts payable to assets	0.08	0.03	0.05	0.22	0.37	0.07	0.02	Thomson Reuters
Accounts receivable	Accounts receivable to assets	0.14	0.06	0.12	0.32	0.07	0.09	0.04	Thomson Reuters
Asset tangibility	Gross property, plant and equipment to assets	0.24	0.08	0.17	0.73	0.10	0.21	0.05	Thomson Reuters
R&D expense	R&D expense to assets	0.04	0.00	0.01	0.18	0.21	0.08	0.02	Thomson Reuters
Market share (%)	Firm sales to total industry sales	0.80	0.05	0.15	3.51	2.30	2.03	0.56	Thomson Reuters
Cash holdings	Cash to assets	0.19	0.04	0.12	0.61	0.20	0.20	0.08	Thomson Reuters
Profitability	Operating income to assets	0.08	0.05	0.09	0.25	0.14	0.13	0.09	Thomson Reuters
Growth opportunities	Market to book of assets	4.27	1.75	2.72	12.35	5.62	4.77	3.89	Thomson Reuters
Lifecycle indicator	Lifecycle indicator based on MLDA	2.83	2.00	3.00	4.00	0.79	0.56	0.64	Thomson Reuters
RE/TE	Retained to total equity	0.36	0.10	0.62	2.10	1.21	1.17	0.51	Thomson Reuters
TE/TA	Total equity to book assets	0.50	0.35	0.49	0.87	0.21	0.20	0.10	Thomson Reuters
Age of firm	Firm age using incorporation dates	33.07	13.00	22.00	101.00	30.18	28.62	3.69	Thomson Reuters
Firm growth	One-year growth in assets	0.10	(0.01)	0.06	0.50	0.22	0.12	0.20	Thomson Reuters
Dividend-only	Equals 1 if the firm pays a dividend only	0.14	0.00	0.00	1.00	0.34	0.23	0.26	Thomson Reuters
Repurchase-only	Equals 1 if the firm repurchases only	0.23	0.00	0.00	1.00	0.42	0.32	0.28	Thomson Reuters
Dividend and repurchase	Equals 1 if firms pays a dividend and repurchases	0.39	0.00	0.00	1.00	0.49	0.38	0.29	Thomson Reuters
Financing constraints	Size-age index of financing constraints: (−0.737* Size) + (0.043* Size2) − (0.040*Age)	(1.69)	(2.69)	(1.53)	0.99	1.75	1.68	0.43	Thomson Reuters
External financing dependence	CAPEX less NCFO divided by CAPEX	(1.76)	(4.26)	(1.75)	4.23	11.46	11.09	7.13	Thomson Reuters
Industry dummies	Industry dummies based on ICB	nm	nm	nm	nm	nm	nm	nm	Thomson Reuters

Number of annual observations

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Observations	658	686	685	691	753	760	854	889	932	901	1010	1043	1041	1044
%	5.51	5.74	5.73	5.78	6.30	6.36	7.15	7.44	7.80	7.54	8.45	8.73	8.71	8.74

3.2. Econometric methodology

The most common approach, in the extant literature, to estimating the relationship between systemic risk and firm-level characteristics has been to use fixed effects regression methods on a panel of data (e.g. Iqbal et al., 2015; Laeven et al., 2016; Anginer et al., 2018; Bostandzic and Weiß, 2018, among others). However, this approach focuses exclusively on the 'within-effect' (i.e. the build-up of systemic risk over time) and removes any 'between-effects'. Consequently, these studies identify the dynamic drivers of systemic risk but are unable to identify the causes of long-term (or average) differences between firms. An alternative approach, used by Calluzzo and Dong (2015), is to estimate pooled OLS regressions but this approach implicitly assumes that the between- and within-effects are the same and where this is violated, the estimated coefficients are some weighted average of the two and are uninterpretable. From Table 4, it is clear that the between- and within- standard deviations of our dependent variables are different and therefore we need a different estimation technique. Ideally, we would like to simultaneously estimate the between- and within-effects of our regressors on systemic risk and, therefore, identify the factors driving long-term differences between firms and short-term, dynamic differences within firms. Bell and Jones (2015) propose the REWB regression which allows us to do this. With REWB regressions, the cross-sectional and longitudinal relationships between systemic risk and each risk predictor are modelled simultaneously by including the risk predictors twice in the regression; first as demeaned terms $(x_{it} - \overline{x_i})$, and second, as firm-level means (of each time-varying variable), $\overline{x_i}$.

$$y_{it} = \beta_0 + \beta_1 (x_{it} - \overline{x_i}) + \beta_2 \overline{x_i} + \mathrm{Year}_t + Industry_j + (u_i + e_{it}) \tag{5}$$

where y represents either MES or ΔCoVaR. β_1 and β_2 capture the longitudinal (within-effect) and the cross-sectional (between-effect) effects on systemic risk, respectively. The REWB approach is very flexible and produces exactly the same estimate (and standard deviation) for β_1 (the within-effect), while retaining and utilising cross-sectional information. Furthermore, it also allows us to check if the two effects are equal (i.e. $\beta_1 = \beta_2$) as implicitly assumed by pooled OLS. This restriction is rejected in all our specifications, so we adopt the REWB approach throughout our empirical analysis.[7]

4. Discussion of results

The REWB regressions are estimated by GLS and our results are presented in Sections 4.1–4.3 and in Tables 5-7.

4.1. Firm-level characteristics associated with MES

We begin with an analysis of the MES systemic risk measure and seek to identify firm characteristics associated with vulnerability to a system-wide shock. Our results are presented in Table 5. Regression 1 relates MES to a range of firm-specific variables. Regression 2 adds variables to capture financing constraints and dependence on external financing, but their inclusion necessitates the exclusion of some other variables used in their construction. Regression 3 adds a corporate governance measure to regression 1 but the variable is unavailable for some firms, so our sample is reduced. Notably, all our regressions show a better fit for the cross-sectional analysis compared to the within-firm regression.

Firstly, we focus on variables associated with the differences *between* firms (columns 2, 4 and 6). Our results show that firm-specific measures of firm risk, VaR and Beta, are positively related to MES. Firms that are individually riskier (as measured by VaR) and firms that are more sensitive to market movements (Beta) tend to be more vulnerable to systemic shocks. However, these measures do not capture all of the firm-specific variables that are associated with this dimension of systemic risk. We find statistically significant evidence that the firm size, debt, accounts receivable, asset tangibility, cash holdings and financing constraints are positively related to MES, i.e. heighten the sensitivity of firms to an economy-wide adverse shock, with more limited evidence that foreign sales behaves in a similar way. On the other hand, higher market share reduces MES and is associated with greater resilience to a systemic shock. None of the other variables exhibit a statistically significant relationship with MES.

Firm size is positively related to MES. This shows that bigger NFCs are more exposed to market shocks, just as with their financial counterparts. It implies that it is not just the expectation of a government bail-out that makes larger firms more associated with systemic vulnerability. However, this is partially offset by the negative relationship between MES and market share. Having a greater share of your market makes firms less replaceable and thereby more resilient to systemic shocks. Hence there is a trade-off in terms of systemic vulnerability between the absolute size and the relative (to competitors) size of NFCs.

The systemic importance of financial debt provides supporting evidence for the IMF warning that corporate indebtedness represents a looming danger to the global economy. Firms who carry a larger debt burden are more vulnerable to a common economic shock. This is likely to be due to a combination of increased difficulty in servicing the debt and higher rollover risk if the debt matures within a crisis period. The current low interest rate environment and favorable tax treatment of debt make debt financing an attractive vehicle for many NFCs. However, with debt levels among US corporates reaching record levels, this result should serve as a warning to both borrowers and lenders as to the potential adverse consequences that this may inflict on the financial system and the wider economy. Debt maturity does not appear to have a statistically significant association with differences in systemic risk between firms in this specification.

We find that trade credit also matters for systemic vulnerability through the significance of accounts receivable in our MES regressions. The trade finance literature implies that firms can be systemically important, regardless of whether they are net trade lenders or borrowers. The former group act as 'banks' for other non-financial firms and their importance is due to the credit that they provide, while the latter rely on that credit and may create systemic problems if and when they default on this debt. The vulnerability of firms with high trade credit linkages is similar to the 'balance sheet contagion' effects that is described as a shock propagation mechanism in Kiyotaki and Moore (2002). Both Hazama and Uesugi (2017), using an extensive network of Japanese firms, and Jacobson and von Schedvin (2015) for Sweden provide empirical evidence of this type of default propagation through trade credit. Corporate defaults impact on trade creditors increasing their likelihood of default. Our results show that trade lenders are most at risk to a systemic shock, i.e. the more trade credit extended, the more vulnerable a firm is to a systemic event. This shows that it's not just connections with the financial system that determine a firm's systemic vulnerability but that, also, linkages between non-financial firms can heighten the sensitivity to a systemic shock.

The positive relationship between MES and cash holdings may, at first, seem counter intuitive since higher cash reserves have traditionally been viewed as a buffer against a systemic shock. However, Acharya et al. (2012a) shows that the relationship between cash holdings and credit risk is consistently positive. They build a theoretical model to explain this phenomenon and provide empirical evidence consistent with its predictions. The model builds on the precautionary motive for holding cash whereby firms who are nearer to default accumulate cash in an effort to bolster their financial position. The probability of default may fall in the short-term but increases at longer-term horizons. Almeida et al. (2004) also finds that financially constrained firms are more likely to save cash out of

[7] Random effects estimation produces coefficients which are a complex weighted average of the within and between effects, which render the coefficients largely uninterpretable.

Table 5
MES and firm fundamentals.

	Regression 1		Regression 2		Regression 3	
	Between	Within	Between	Within	Between	Within
VaR	0.310*** (11.48)	0.221*** (19.29)	0.287*** (10.70)	0.221*** (19.45)	0.264*** (7.80)	0.248*** (14.10)
Beta	0.409*** (8.52)	0.062*** (2.63)	0.420*** (8.70)	0.063*** (2.65)	0.527*** (8.62)	0.105*** (2.64)
Log (firm size)	0.081*** (5.29)	0.132*** (2.64)			−0.011 (0.55)	0.063 (1.24)
Debt	0.104** (2.05)	0.217*** (3.94)	0.155*** (3.21)	0.236*** (4.20)	0.138** (2.38)	0.257*** (3.85)
Debt maturity	0.030 (0.50)	0.050 (1.00)	0.101* (1.74)	0.059 (1.19)	0.090 (1.01)	0.124* (1.76)
Accounts payable	−0.258 (1.26)	0.382 (0.78)	−0.257 (1.26)	0.275 (0.55)	−0.216 (0.81)	0.564 (0.87)
Accounts receivable	0.638*** (3.62)	0.779** (1.97)	0.504*** (2.93)	0.678* (1.73)	0.620*** (2.68)	0.697 (1.26)
Log (firm age)	−0.013 (0.76)	0.205*** (3.15)			−0.017 (0.76)	0.073 (0.99)
Asset tangibility	0.252*** (2.71)	0.176 (0.65)	0.233** (2.46)	0.173 (0.64)	0.169 (1.38)	0.743** (2.01)
R&D expense	0.798* (1.69)	−0.411 (0.59)	0.726 (1.54)	−0.319 (0.46)	1.366** (2.35)	−1.385 (1.15)
Market share	−0.027*** (4.68)	−0.003 (0.21)	−0.010** (2.22)	0.009 (0.57)	0.001 (0.20)	0.010 (0.66)
Cash holdings	0.261* (1.69)	0.282 (1.53)	0.281* (1.80)	0.212 (1.14)	0.526** (2.48)	0.392** (2.14)
Profitability	−0.199 (0.83)	−0.167 (0.97)			−0.946*** (3.10)	−0.205 (0.88)
Growth opportunities	0.004 (1.12)	0.006** (2.28)	0.004 (1.09)	0.002 (0.77)	0.000 (0.05)	0.002 (0.82)
Foreign sales	0.052 (0.82)	0.123 (0.87)	0.105* (1.67)	0.143 (1.02)	0.112 (1.26)	0.301** (1.98)
Dividend-only	0.019 (0.27)	0.019 (0.31)	0.008 (0.12)	0.032 (0.53)	−0.074 (0.69)	−0.118 (1.35)
Repurchase-only	−0.130* (1.77)	0.057 (1.45)	−0.114 (1.59)	0.061 (1.53)	−0.113 (1.17)	−0.027 (0.45)
Dividend and repurchase	−0.039 (0.59)	−0.025 (0.43)	−0.036 (0.58)	−0.011 (0.19)	−0.119 (1.39)	−0.086 (1.05)
External financing dependence			0.002 (0.77)	−0.002 (1.02)		
Financing constraints			−0.035*** (3.19)	−0.133** (2.26)		
Corporate governance					−0.073 (0.67)	−0.101 (1.24)

	Regression 1	Regression 2	Regression 3
Time and industry dummies	Included	Included	Included
Observations	11,947	11,947	6394
R-squared (overall)	0.512	0.510	0.532
R-squared (between)	0.587	0.583	0.602
R-squared (within)	0.458	0.456	0.437

Industry effects (from regression 1) (technology is the reference group)

Telecommunications	Health Care	Consumer Discretionary	Consumer Staples	Non-financials	Basic Materials	Energy
−0.288*** (3.40)	−0.461*** (8.21)	−0.174*** (3.28)	−0.607*** (9.52)	0.044 (0.90)	0.026 (0.34)	0.024 (0.30)

This table reports coefficient estimates from a series of random effects within between (REWB) regressions with robust standard errors. The dependent variable is marginal expected shortfall. The sample includes publicly traded non-financial U.S. firms over the period 2004–2018. We define all variables in Table 1. With the exception of firm age, we lag by one year all independent variables. ***, **, and * denotes statistical significance at the 1, 5, and 10% levels, respectively.

cash flow. Our result is consistent with this. Firms with higher levels of cash are already close to (or in) financial distress and tend to be more vulnerable to a system-wide shock.

The positive sign on asset tangibility is at odds with the evidence on individual firm risk. At the firm level, higher levels of asset tangibility are usually considered to be risk reducing as physical assets can be liquidated if necessary or help to maintain debt capacity through the collateral they offer to secure loans (Kiyotaki and Moore, 1997). While this is true at the firm level, we find the opposite effect at the system level,[8] with greater levels of asset tangibility being associated with greater vulnerability to systemic risk. This is possibly due to the increased illiquidity of these asset types during an economic downturn when firms may be forced to divest assets in periods of low demand. Deleveraging during a crisis results in large haircuts on asset values, producing downward price spirals or cascades (Shleifer and Vishny, 2011). Hence, holding tangible assets can increase systemic vulnerability despite reducing risk during normal time periods.

A number of variables are significant in one specification only. Increasing financing constraints reduces the vulnerability to a systemic shock. This implies that firms with reduced access to finance sources suffer relatively less when there is a market downturn as they are more decoupled from the market in all market conditions. Among our dividend payout mechanism, only firms who limit themselves to repurchasing shares appear to be different in terms of their systemic vulnerability. These firms are associated with lower MES, arguably due to the lower commitment to distribute cash and thereby the greater flexibility to divert funds during crisis periods. Finally, foreign sales is marginally significant in the second regression, suggesting that firms with greater international exposure are more systemically vulnerable. This suggests that the market risk channel is relatively more important than the diversification channel in determining systemic vulnerability.[9]

[8] Wagner (2010) has already shown, for banks, that actions which may make the individual more resilient can have the opposite effect on the financial system.

[9] Berger et al. (2017) find that internationalisation is also positively related to bank risk.

Table 6
ΔCoVaR and firm fundamentals.

	Regression 1		Regression 2		Regression 3	
	Between	Within	Between	Within	Between	Within
VaR	−0.026*** (5.39)	0.025*** (10.49)	−0.039*** (7.58)	0.025*** (10.38)	−0.036*** (6.38)	0.038*** (9.86)
Beta	0.047*** (5.16)	−0.002 (0.37)	0.050*** (5.52)	−0.004 (0.69)	0.059*** (4.40)	0.003 (0.39)
Log (firm size)	0.042*** (11.28)	0.078*** (8.62)			0.025*** (5.50)	0.076*** (5.74)
Debt	−0.028*** (2.58)	−0.095*** (8.07)	−0.011 (0.99)	−0.102*** (8.45)	−0.016 (1.53)	−0.095*** (6.38)
Debt maturity	0.010 (0.95)	−0.019 (1.62)	0.031** (2.31)	−0.019 (1.61)	−0.004 (0.32)	0.004 (0.25)
Accounts payable	−0.143** (2.37)	−0.107 (0.93)	−0.153** (2.54)	−0.148 (1.26)	−0.073 (1.21)	−0.105 (0.69)
Accounts receivable	0.159*** (3.57)	0.071 (0.81)	0.120*** (2.64)	0.114 (1.26)	0.141*** (2.86)	0.074 (0.54)
Log (firm age)	0.013*** (3.48)	0.036** (2.21)			0.012*** (2.84)	0.023 (1.06)
Asset tangibility	−0.006 (0.27)	−0.045 (0.70)	−0.003 (0.13)	−0.066 (1.02)	−0.029 (1.00)	−0.072 (0.84)
R&D expense	−0.023 (0.23)	−0.083 (0.66)	−0.123 (1.48)	−0.198 (1.46)	0.018 (0.21)	0.052 (0.22)
Market share	−0.002 (1.11)	0.005 (1.18)	0.006*** (5.13)	0.012*** (2.85)	0.003* (1.84)	0.005 (1.11)
Cash holdings	0.005 (0.20)	0.056 (1.37)	0.022 (0.71)	0.049 (1.11)	−0.020 (0.60)	0.059 (1.20)
Profitability	0.044 (1.10)	0.161*** (4.89)			−0.066 (1.07)	0.225*** (4.75)
Growth opportunities	0.001 (0.54)	0.003*** (3.98)	0.001 (0.88)	0.003*** (3.80)	0.000 (0.06)	0.002** (2.44)
Foreign sales	0.027* (1.74)	0.071*** (3.01)	0.049*** (3.07)	0.075*** (3.02)	0.049** (2.28)	0.062* (1.70)
Dividend-only	0.065*** (3.76)	0.010 (0.70)	0.062*** (3.67)	0.011 (0.80)	0.047** (2.25)	0.011 (0.50)
Repurchase-only	0.020 (1.56)	0.025*** (2.64)	0.034** (2.44)	0.026*** (2.81)	0.004 (0.52)	0.033** (2.01)
Dividend and repurchase	0.076*** (5.26)	0.023* (1.69)	0.081*** (5.78)	0.028** (2.14)	0.050*** (3.02)	0.035 (1.58)
External financing dependence			0.000 (0.90)	−0.001*** (2.70)		
Financing constraints			−0.028*** (9.72)	−0.096*** (8.68)		
Corporate governance					0.003 (0.10)	0.039 (1.64)
Time and industry dummies	Included		Included		Included	
Observations	11,947		11,947		6394	
R-squared (overall)	0.803		0.800		0.827	
R-squared (between)	0.767		0.754		0.766	
R-squared (within)	0.813		0.812		0.838	

Industry effects (from regression 1) (technology is the reference group)

Telecommunications	Health Care	Consumer Discretionary	Consumer Staples	Non-financials	Basic Materials	Energy
−0.043** (2.37)	−0.048** (2.46)	−0.052*** (4.01)	−0.140*** (8.92)	0.034*** (3.17)	0.032* (1.87)	0.021 (1.44)

This table reports coefficient estimates from a series random effects within between (REWB) regressions with standard errors robust to sampling error in ΔCoVaR using the approach of Lewis and Linser (2005). The dependent variable is ΔCoVaR. The sample includes publicly traded non-financial U.S. firms over the period 2004–2018. We define all variables in Table 1. With the exception of firm age, we lag by one year all independent variables. ***, **, and * denotes statistical significance at the 1, 5, and 10% levels, respectively.

Regression 3 reveals that corporate governance is not statistically significant in our between-firm regression specifications.[10] This is an interesting difference between our results and the extant literature on financial firms where, for example, both Iqbal et al. (2015) and Anginer et al. (2018) report that better corporate governance is associated with higher levels of systemic risk. This is often attributed to higher risk taking among institutions whose goals are more aligned with shareholders and can be, again, related to the expectation that financial firms will not be allowed to fail. It appears that the absence of such an expectation among NFCs results in no significant relationship between corporate governance and MES for non-financial firms.

There exists sizable intra-industry differences in risk exposure; firms in the technology, industrials, and basic materials are most exposed to systemic risk. Consumer staples and healthcare appear to be least sensitive to a market downturn. Differences in MES between industries are economically large; for instance, the difference in MES between technology and consumer staples is 0.607 or 22.15% of average MES. Our industry findings align with those of Kerste et al. (2015) for the energy sector and Behrens et al. (2013) which shows that producers of consumer durables, intermediates and capital goods in Belgium experienced much larger falls in exports between 2008 and 2009. In a similar vein, Engle and Wang (2011) find that trade in durables and other non-essential goods are more adversely affected by demand shocks.

The within-firm estimates, which capture the build-up of systemic risk (columns 3 and 5), show that it is mainly the same set of variables that are associated with systemic vulnerability over time. Once more, VaR, Beta, size, debt and accounts receivable are all positively related to MES over time, while market share, cash holdings and asset tangibility are not statistically significant in the within-firm regressions. In addition to these variables, there is some evidence that debt maturity also matters with firms with longer maturity debt being more susceptible to a market downturn. It may be that the increased monitoring of short-term debt keeps firms less risky and better prepared to deal with an adverse systemic shock. Likewise, firms with greater growth opportunities are also associated

[10] For a reduced sample for which we have information on managerial entrenchment, we also use this as a proxy for corporate governance. Our results are unchanged and are available from the authors upon request.

Table 7
Systemic risk and firm lifecycle.

	Dependent variable is MES				Dependent variable is ΔCoVaR			
	Lifecycle is RE/TE		Lifecycle is MLDA lifecycle		Lifecycle is RE/TE		Lifecycle is MLDA lifecycle	
	Between	Within	Between	Within	Between	Within	Between	Within
RE/TE	0.0001 (0.68)	−0.0003 (1.09)			0.0002*** (3.88)	0.0000 (0.14)		
Growth-stage			−0.175 (1.54)	0.011 (0.14)			−0.032 (1.33)	0.041** (2.38)
Mature-stage			−0.318** (2.55)	−0.014 (0.17)			0.040 (1.50)	0.051*** (2.82)
Shake-out/decline-stage			−0.357*** (2.94)	−0.015 (0.19)			−0.062** (2.41)	0.025 (1.45)

Time and industry dummies	Included	Included	Included	Included
Control variables	Included	Included	Included	Included
Observations	11,947	11,947	11,947	11,947
R-squared (overall)	0.512	0391	0.803	0.746
R-squared (between)	0.593	0.621	0.769	0.780
R-squared (within)	0.457	0.325	0.812	0.747

Testing for differences across MLDA lifecycle stages								
Growth-stage vs. mature-stage							***	
Growth-stage vs. SO/decline stage			**					*
Mature-stage vs. SO/decline stage							***	***

This table reports coefficient estimates from a series random effects within between (REWB) regressions with robust standard errors. The dependent variable is MES and ΔCoVaR, as indicated. The sample includes publicly traded non-financial U.S. firms over the period 2004–2018. Firm lifecycle is measured using each of RE/TE and MLDA lifecycle, as indicated. Where RE/TE is included, TE/TA is simultaneously included, but not reported. We define all variables in Table 1. ***, **, and * denotes statistical significance at the 1, 5, and 10% levels, respectively.

with greater MES. These firms are likely to have less free resources to insulate themselves from the downturn and hence exhibit greater vulnerability to a market-wide shock.

As well as being statistically significant, our between- and within-estimates are also economically significant. For instance, in the cross section of firms, the effects of both VaR and equity Beta on MES are large; a one-standard deviation change in each variable causes MES to change in the region of 12.6% and 9.1% of average MES, respectively.[11] The influence of other variables such as debt (1.9%), accounts receivable (1.9%), R&D (2.8%), financing constraints (2.1%), and asset tangibility (1.7%) are lower but not trivial. Likewise, within-firm estimates produce similarly large economic effects. In this dimension, a one standard deviation change in VaR yields an average within-firm change in MES of 13.5%, while the influence of beta (1.4%), accounts receivable (1.0%), and debt (2.5%) are not insignificant.

4.2. Firm-level characteristics associated with ΔCoVaR

Now, we turn our attention to ΔCoVaR, which captures the contribution of individual firms to systemic risk. Table 6 reports our results.[12] The picture of the type of firm that emerges of an important source of systemic risk is different from the type of firm that is vulnerable to a systemic crisis, which is consistent with the evidence of Table 2 and Fig. 3. Again, we start with '*between-firm*' differences. VaR and Beta both matter. Firms that are more connected with the market tend to have higher systemic contribution, while firms with higher VaR tend to have lower ΔCoVaR. The latter is often interpreted as idiosyncratic risk (e.g. Van Cauwenberge et al., 2019) which the financial system can diversify away, thus reducing their impact on the greater economy. The contribution of non-financial firms to systemic risk is positively related to size, both in the absolute sense (assets) and relative to competitors (market share). This result is in line with previous analysis of financial firms and shows that larger non-financial firms contribute more to systemic episodes than smaller firms and is consistent with Ferris et al. (1997) which has shown that dominant firms are more important within an industry. This can be due to their individual size or the linkages they have with other parts of the system. Likewise, firm age is positively associated with systemic contribution, implying that when older firms suffer an adverse shock, it has greater

[11] The REWB methodology allows us to differentiate between the economic significance of variable changes in the cross-section and time dimensions, since we estimate separate standard deviations. This is an advantage of the methodology over pooled regressions where the within-firm standard deviation is often overestimated, see De Haan (2021). When firm-level characteristics are included in more than one regression specification, we take the average value of the estimated coefficients to compute the economic significance of the variable.

[12] Since our dependent variable in these regressions has been generated from a first-step procedure, we correct the standard errors of these estimates using the Lewis and Linzer (2005) methodology.

impact on the financial system than for younger firms. Interestingly, firms with greater foreign sales also tend to have larger ΔCoVaR. Given their greater geographical coverage, large negative shocks to these firms may be interpreted as a more global shock and more difficult to hedge against.

In general, dividend-paying firms (whether dividend only or in combination with share repurchases) are associated with higher contribution to systemic risk. Though not contractually obliged to do so, it is generally accepted that firms are reluctant to cut dividends due to the adverse signal that it transmits to the investment community (Brav et al., 2005).[13] Therefore, dividend payers are likely to require a greater proportion of cash resources and thus reduce cash available for other system-wide activities. Furthermore, the IMF (2019) reports an increasing tendency for firms to fund dividend payouts by borrowing. Such dividends are unsustainable (without growth), implying that an economic downturn is likely to raise the systemic contribution of these firms.

The relationship between systemic contribution and debt (financial and trade) is interesting. Higher contributors to systemic risk appear to use less financial debt as the estimated coefficient on our debt variable is consistently negative, though only significantly different from zero in regression 1. This suggests that the financial system is already taking systemic contribution into account when issuing financial loans and extending greater credit to firms who are less likely to contribute to system-wide financial distress. Consequently, the dangers from increasing corporate indebtedness may not be as damaging to the overall economy, as predicted by the IMF (2019). Our results suggest that there are feedback effects between ΔCoVaR and debt with providers of credit proving to be adept at identifying more systemically important borrowers and limiting their exposure to these firms. In unreported results, we reverse the causality and use the debt ratio as our dependent variable and find that the coefficient on lagged ΔCoVaR is indeed negative and statistically significant.[14] We also check the robustness of this result, using a range of other definitions of debt, e.g. debt to assets, log of debt, and establish that the reported relationship is unaffected by the debt variable employed.

Trade credit variables show that there is a nuanced relationship with systemic risk. Accounts payable, which measures trade debt, follows a similar pattern to financial debt. Firms with greater systemic contribution appear to benefit less from trade credit implying that 'lenders' are well-positioned to differentiate between 'good' and 'bad' credit risks and are adept at reducing their exposure to NFCs with higher systemic contribution. In contrast, firms that extend more trade credit, captured through accounts receivable, are associated with higher contribution to systemic risk, showing that 'lenders' are systemically important in both dimensions. A negative shock to such a company increases the risk of the system, acting like a non-monetary liquidity effect. A downturn in the fortunes of such a firm makes it more difficult for others to operate given that trade credit may be restricted or more costly in the future. For example, Hasan et al. (2020) present evidence that financial institutions use information about trade credit providers (input suppliers) to assess the creditworthiness of its customers. Overall, a negative shock to firms who act as trade banks is more threatening to the health of the financial system than a negative shock to firms who avail of trade credit.

Regression 2 shows some evidence that debt maturity is positively associated with ΔCoVaR, implying that firms with longer-dated debt have higher systemic contribution. These firms are usually expected to possess favorable credit credentials and would not be subject to the frequent monitoring of short-term debt rollovers. Hence, negative surprises to these firms could have a relatively stronger effect on the financial system. In this specification, we also show that more financially constrained firms have less systemic contribution, which is consistent with these firms being less connected to the market.

For ΔCoVaR and the time dimension of systemic risk, we find that, for some firm-level characteristics, the *within-firm* effects are quite different from the *between-firm* effects already discussed. Whereas idiosyncratic risk (VaR) is associated with lower systemic contribution in the cross-section of firms, we find that for the average firm, firm-specific risk is positively related to ΔCoVaR over time. In contrast, Beta is not statistically significantly related to ΔCoVaR, possibly due to a lack of variation over time. This reveals an important feature of our estimation technique as it is capable of disentangling the cross-sectional and longitudinal relationships between variables, revealing important differences between the role of these measures of individual firm risk in contributing to systemic events in the cross-section of firms and in the build up to market downturns.

A number of variables display the same relationship with systemic risk in both dimensions of the measure. Foreign sales, firm size, market share (when size is omitted), and firm age are all positively related to the evolution of systemic risk for the average firm, while financial constraints are again negatively related to systemic contribution. As in the cross-sectional analysis, there is a negative relationship between financial debt and systemic risk. A similar result is reported for Dutch NFCs in Van Cauwenberge et al. (2019) who argue that it is due to the restriction of credit during systemic events, so again consistent with the argument there are bilateral feedback effects between financial debt and systemic risk. In this within-firm analysis, trade credit variables are not statistically different from zero, showing that their association to systemic contribution is limited to the cross-sectional dimension of systemic risk.

Payout variables differ in the time dimension. Dividend payers, probably due to the lack of variability in the variable due to the persistence of dividends once initiated, are not related to systemic contribution but now firms who engage in share repurchases have a statistically significant and positive association with ΔCoVaR. Share repurchases tend to be lumpy and reversible but divert liquid assets from the system to shareholders which may accentuate the negative effects of a financial downturn. Profitability and growth opportunities matter in the build-up of systemic contribution over time. Both variables are positively related to ΔCoVaR over time. As profits grow, firms become more important to the system so any negative shocks to these firms impact more to the overall market. Likewise, with growth opportunities, firms with higher increasing market to book values have higher systemic contribution as a higher proportion of their price is based on the expectation of future performance rather than underlying tangible assets. Finally, firms that

[13] John et al. (2015) places cash dividend payments at the top of a payout precommitment hierarchy, ahead of contractual debt obligations and other forms of cash distribution to stakeholders.

[14] These results are available from the authors upon request.

have increasing financial constraints are associated with falling contribution to systemic risk as they become more decoupled from the market.

Once more, there is substantial intra-industry variation in the contribution to systemic risk. Now, we find that basic materials, industrials, energy and technology are the industries which contribute most to systemic downturns. The first two sectors tend to be labour intensive and negative shocks to these industries are likely to produce adverse effects for the real economy. The health of the energy and technology sectors may be seen as leading indicators of the general economic health and negative news emanating from these industries may be a forerunner to a downturn in the general economy. Differences in systemic risk contribution between industries are economically significant; for example, the difference in ΔCoVaR between technology sector and consumer staples firms is 0.140 or 17.4% of average systemic risk.

As was the case with our MES estimates, our ΔCoVaR estimates are economically and statistically significant. In the cross-sectional dimension, a one-standard deviation change in firm-level characteristics can account for large differences in ΔCoVaR between-firms, e.g. size is associated with a change in average ΔCoVaR of approximately 6.7%, while financing constraints (5.8%), VaR (5.0%), and beta (3.5%) all matter. Similarly, economically significant changes in ΔCoVaR within-firms are found for each of VaR (5.8%), financing constraints (5.1%), size (4.4%), debt (3.5%), and profitability (2.1%).

4.3. *Systemic risk over the lifecycle*

Regression results in Tables 5 and 6 show that firm age is statistically significantly related to both MES and ΔCoVaR. We want to investigate if this variable is a proxy for the firm lifecycle as it sometimes used as such in other studies, e.g. Faff et al. (2016) among others. We use two measures of firm lifecycle. Firstly, we include the ratio of retained to total earnings (RE/TE) as proposed by DeAngelo et al. (2006) who argue that this ratio should increase as firms mature. Secondly we use the MLDA methodology of Faff et al. (2016) to classify firms into a lifecycle stage (as outlined earlier) and then estimate a series of REWB regressions with the birth stage being the omitted reference group. Our results are reported in Table 7[15] and are consistent with the fact the firm age may be a proxy for a lifecycle effect.

We find evidence of a lifecycle effect for MES and ΔCoVaR, especially when we use the MDLA methodology to classify firms. Focusing on MES, we find strong evidence of a lifecycle effect in the cross-sectional analysis. Specifically, relative to the birth stage, firms in each of the later stages of the lifecycle spectrum are more resilient to systemic risk and exhibit a U-shaped pattern. Vulnerability to a systemic event is greatest for birth-stage firms and this declines as the firm progresses along the lifecycle with the peak resilience occurring in the mature stage. Thereafter, vulnerability again increases in the shake-out and decline stage but remains lower than in the birth stage and is not statistically different from the growth stage. In other words, a systemic crisis is most likely to affect younger, early-stage firms and firms who have already entered into their decline stages. This is consistent with the extant literature which has shown that beta and tail risk peak in early-stage firms and fall as firms age (see Chincarini et al., 2016; and Habib and Hasan, 2017). Younger firms are particularly dependent on external financing and are likely to be most adversely affected by turbulence and frictions in debt markets, particularly in securing bank loans at affordable rates. Economic downturns and recessions are also difficult times to release new products on the market and are likely to impact more negatively on new companies whose brand may not yet be recognisable to potential customers.

For ΔCoVaR, there is strong evidence of a lifecycle effect in the time dimension and weaker evidence for the cross-sectional analysis. Over time, the average firm appears to become a larger contributor to systemic risk, with increases in ΔCoVaR as firms progress from birth to growth and through to the mature stage of their lifecycle. The peak is during this mature stage. Between-firm differences in ΔCoVaR do not show any strong lifecycle effect but there is evidence that RE/TE increases with ΔCoVaR, consistent with the argument that firms become more systemically important as they progress over the lifecycle. However, there is no statistical evidence of such a pattern in the MDLA classification.

5. Conclusion

This paper examines the systemic risk of large U.S. non-financial firms and establishes that such firms can be of systemic importance. NFCs, through their interactions with the financial system and with each other, can both exhibit high vulnerability to a systemic shock and contribute to the systemic event through the transmission of its own shocks. This aspect of systemic risk has received relatively little attention in the academic literature and its role in propagating systemic events needs to be understood. We find that, generally, firms who are most vulnerable to a crisis are different from those who generate systemic risk but they share some common characteristics. Interestingly, there is greater consistency at the industry level, with technology, energy, industrials and basic materials being more systemic that other sectors. In common with the literature on financial institutions, firm size matters with larger firms being more systemically important in both dimensions of the risk. Individual risk measures are also associated with systemic risk, with firms with higher market risk (beta) having higher systemic vulnerability and contribution, while firms with more idiosyncratic risk tend to be more vulnerable, but contribute less, to market-wide downturns.

The relationship between financial debt and systemic risk is interesting, especially in the light of the IMF (2019) report on the dangers of the increasing reliance of NFCs on debt financing. Our results suggest that this risk falls mainly on the corporations

[15] All regressors from earlier regression are included as control variables with the exception of firm size, age and profitability which are used in the allocation of firms to each of the lifecycle stages using MLDA.

themselves as debt is positively related to systemic vulnerability but negatively related to systemic contribution. It appears that the financial system is effectively protecting itself from the highest contributors to systemic shocks and already taking this dimension of systemic risk into account when issuing loans to NFCs. We also find evidence that trade debts – accounts receivable and payable – are related to systemic importance, particularly accounts receivable suggesting that providers of credit are relatively more crucial for the stability of the overall system.

Overall, this study shows that NFCs are systemically important, and this risk needs to be managed by financial institutions and providers of trade credit. The identification of firm-level characteristics that are associated with higher levels of systemic risk can provide a picture of what systemically important NFCs look like. Many variables have a nuanced relationship with systemic risk measures. For example, there are variables that matter for within-firm variation in systemic risk measures but are unimportant in the cross-sectional analysis (e.g. growth opportunities), while others display the reverse pattern (e.g. payout-related variables, such as dividends). Asset tangibility is an example of a factor that exerts differential effects at the individual and system level. Higher asset tangibility is typically found to reduce risk at the firm-level but we find that it is associated with increases in both dimensions of systemic risk, possibly due to the difficulty in realising their book values during a crisis episode, especially if the seller has been forced to divest these assets to dedebt.

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