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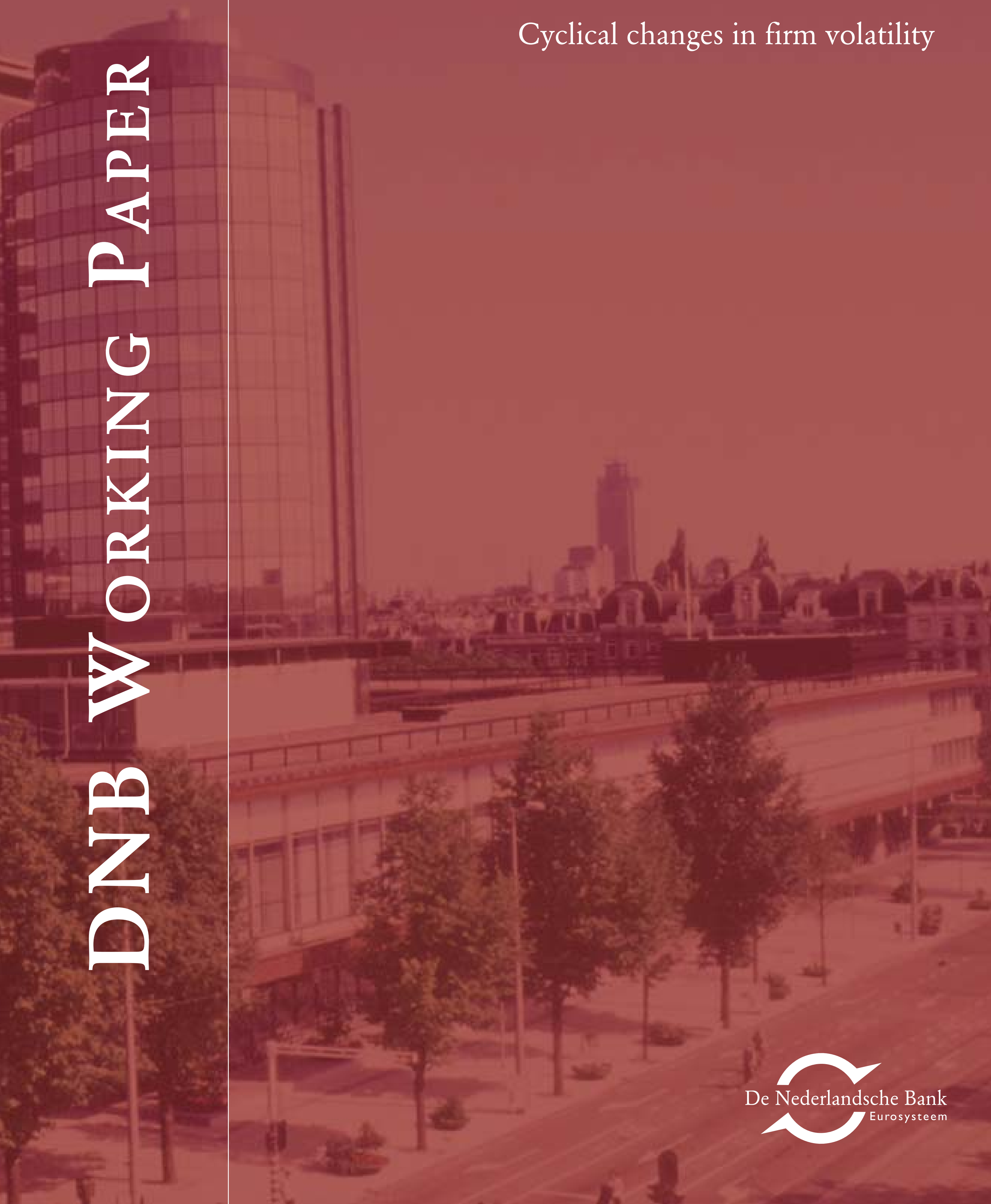

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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Cyclical Changes in Firm Volatility*

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Abstract

We estimate changes in firm-specific volatility in sales and earnings growth of US firms. We do so using an approach which better captures firm-specific volatility than commonly used dispersion measures do. Our results do not lend strong support to the common view that firm-specific volatility is counter-cyclical. The role of firm-specific volatility in explaining aggregate fluctuations is empirically very limited. This is evidence against the implication of irreversibility and financial accelerator theories that increases in firm-specific volatility cause macroeconomic downturns. Our measure also provides evidence on trends in firm volatility. Earlier findings of a trend increase in the volatility of publicly traded firms are completely overturned when we control for changes in sample composition. At the firm level, the 2007-2009 recession did not end the Great Moderation.

JEL codes: C32, C33, D22, E32

Keywords: Firm-Level Volatility, firm-specific shocks, business cycles

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1 Introduction

When shocks to firms are more volatile, this can in principle have macroeconomic consequences. There are two prominent sets of theories which imply that rises in firm-specific volatility cause macro-economic downturns. In models with partial irreversibilities in the spirit of Bloom (2009), a temporary rise in firm-specific uncertainty causes firms to postpone investment and hiring, which temporarily slows down the aggregate economy.[1] In some models with financial frictions, including that of Christiano, Motto, and Rostagno (2013), a rise in the volatility of firm-specific borrower risk implies an increase in the external finance premium, which causes a slowdown in aggregate growth.[2]

The empirical evidence that motivates these theories implies that firm-level volatility is counter-cyclical, and that changes in firm volatility explain an important part of aggregate fluctuations. This evidence is based either on empirical measures of dispersion in the distribution of firm-level growth rates, or on models that rely exclusively on macroeconomic data to estimate a process for time-varying firm-specific uncertainty.

In this paper, we produce an empirical series from firm-level data which we argue better captures firm-specific volatility than dispersion measures do. We use that series to examine the cyclical properties of firm-specific volatility in sales and earnings growth of US firms.[3]

In terms of contemporaneous associations, we find some evidence that firm-specific volatility is counter-cyclical, although the link is much less strong than it would appear from all earlier evidence we know of that was obtained with dispersion measures. In terms of dynamic interactions, we find

[1] See also Bloom, Floetotto, Jaimovich, Saporta-Eksten and Terry (2012).

[2] Other models with financial frictions where rising firm-specific volatility causes aggregate downturns include Gilchrist, Sim, and Zakrajsek (2010) and Arellano, Bai, and Kehoe (2012). This effect is also present, but quantitatively less important, in Chugh (2009).

[3] De Veirman and Levin (2012) estimate firm-specific volatility of Japanese firms. They do not address the cyclical properties of their estimates of firm volatility.

that firm-specific volatility does not significantly contribute to in-sample fluctuations in aggregate real activity beyond information contained in lagged real growth rates. To the extent that we find any evidence in line with the essential dynamics of the above two types of theories, we find that those dynamics play a small role in explaining credit spreads and play a very small role in explaining fluctuations in real activity.

This finding is at odds with the theoretical prediction that firm-specific volatility is an important driver of the business cycle. It therefore favors models where firm-specific volatility is estimated not to be a major factor behind macroeconomic fluctuations.[4] Since we find do not find a strong and robust dynamic relation in either direction between firm volatility and the business cycle, our results also do not strongly support theories where firm volatility is endogenous to the business cycle.[5]

As for irreversibility theories, we do not test the implication that uncertainty about macroeconomic aggregates drives real growth. Bloom (2009) does test the dynamic interaction of aggregate stock market volatility on the macroeconomy. His results are in line with the implications of irreversibility theories on the effects of macroeconomic uncertainty on the macro-economy.

Our paper also contributes to the literature on trend changes in firm-level volatility. Comin and Philippon (2005) and Davis, Haltiwanger, Jarmin, and Miranda (2006) find that there was a trend increase in the volatility of publicly traded firms, which was mitigated but not fully explained by the time at which a firm first listed.[6] We show that the finding of a trend increase

[4]Bachmann and Bayer (2011) do not find evidence for wait-and-see effects in a model calibrated to German data, while Bachmann, Elstner and Sims (2010) reach the same conclusion with empirical measures of uncertainty based on survey data. The finding by Gilchrist and Zakrajsek (2012) that the risk premium component of credit spreads is a stronger and more robust predictor of real activity than the default-risk component implicitly suggests that firm-specific volatility, which in Christiano, Motto, and Rostagno (2013) affects credit spreads through its effect on default risk, is empirically not the predominant driver of aggregate fluctuations.

[5]These theories include Bachmann and Moscarini (2012), Decker, D'Erasmo and Moscoso Boedo (2013), and Christiano and Ikeda (2013). Kehrig's (2011) model implies endogenous countercyclical dispersion in productivity levels.

[6]See also Comin and Mulani (2006). This literature compares trend developments in firm volatility with a long-

is completely overturned when we control for the effect of changes in sample composition on firm-specific volatility. Our results therefore confirm the intuition of Davis e.a. (2006) that the trend increase in the volatility of US firms reflects a composition effect in that it has tended to become easier for young, typically more volatile, firms to list on US stock markets.[7] The typical publicly traded firm is more stable now that it was at any point since the beginning of our sample period in 1978. At the firm level, the 2007-2009 recession did not end the Great Moderation.

In comparison with common dispersion measures, our technique is a better measure of firm-specific volatility than the cross-sectional standard deviation and the cross-sectional interquartile range, computed on all firms in a sample, for the following reasons. First, dispersion can reflect firm-specific shocks, but it can also reflect differences in responses to common shocks. Our measure filters out these differences that are due to firms being of a different size or a different sector. Second, changes in dispersion can be due to changes in the composition of firms in two respects: new firms may happen to differ more in terms of their typical growth rate, and new firms may happen to differ more in terms of their typical level of volatility. Our estimation procedure controls for both composition effects.

In comparison with rolling standard deviations, which the above-mentioned papers on trends in firm volatility use, our technique has the following advantages. First, it captures the level of volatility at the same frequency of the available data, such that we can draw precise conclusions about the timing of changes in firm volatility. Therefore, we can characterize the cyclical properties of firm volatility in addition to documenting its trend changes. Second, it captures the firm-specific component of firm-level volatility, unlike the rolling standard deviation which mixes firm-specific,

term decline in aggregate volatility known as the Great Moderation. See Davis and Kahn (2008) for an overview and joint interpretation of evidence on changes in aggregate and microeconomic volatility.

[7] See Fama and French (2004) and Brown and Kapadia (2007) for a similar finding for firm-specific stock return volatility.

sector-level and aggregate influences on firm-level growth. Third, rolling standard deviations equally reflect predictable and planned changes as unpredictable changes, while our measure filters out at least some types of predictable changes.

Our econometric approach for estimating firm-specific volatility is related to a literature that estimates time-variation in the volatility of firm-level stock returns, decomposed into firm-specific, sectoral and aggregate volatility.[8]

We use data from Compustat quarterly. We either drop observations that are outside of the normal range of growth rates in any sector or use a growth rate definition where a large change in sales or earnings for a single firm cannot cause a spike in measured volatility or dispersion. This allows us to look at a broader set of measures than only the interquartile range, which is the measure that typically underlies existing evidence on counter-cyclicality of sales growth dispersion. We replicate earlier findings that the interquartile range is counter-cyclical. However, the cross-sectional standard deviation is a-cyclical. The results for our new series of firm-specific volatility are in between those two, in that it is weakly counter-cyclical.

We document that findings by Bloom, Floetotto, Jaimovich, Saporta-Eksten and Terry (2012) that the interquartile range is counter-cyclical are robust to de-trending the interquartile range non-linearly, as well as to cleaning the data by omitting tail observations and to excluding Compustat data for the 1960s and the 1970s. We checked this for the following reasons. Compustat was still substantially expanding coverage in the early decades, which tends to bias the results towards finding low but increasing dispersion since the interquartile range does not intrinsically control for changes in sample composition. Non-detrended dispersion can therefore appear to be correlated

[8] For evidence on changes in the volatility of stock returns in the United States, see Campbell, Lettau, Malkiel, and Xu (2001), Malkiel and Xu (2003), Fama and French (2004), Brown and Kapadia (2007), and Fink, Fink, Grullon, and Weston (2010). Hamao, Mei, and Xu (2007) provide such evidence for Japan. For a similar methodology applied to differences across sectors in the volatility of sales and productivity, see Castro, Clementi, and Lee (2009).

with GDP growth if trend GDP growth is correlated with changes in sample composition. The relative underestimation of dispersion in the early years will tend to imply an upward linear trend in dispersion which causes mis-measurement of de-trended dispersion in later years.

Bloom e.a. (2012) use a sample of long-lived firms in an effort to reduce the effect of changes in sample composition on quarterly changes in the interquartile range. These results for a specific type of firms are not necessarily representative for the overall economy. We show that the interquartile range is not counter-cyclical when firms are included irrespective of the number of available observations in Compustat. Since the interquartile range does not otherwise control for changes in sample composition, this could reflect a cyclical pattern in sample composition if firms that newly list during a boom are volatile compared to previously listed firms, and if these volatile firms are also more likely to delist than other firms during recessions.

Our main results are therefore based on a cleaned sample without any requirement for included firms to be long-lived, and with our measure of firm-specific volatility that controls both for trend and cyclical changes in sample composition. We find that de-trended firm-specific volatility tends to peak around the time of recessions. These peaks occur up to four quarters before the beginning, and up to four quarters after the end of a recession. However, there is little evidence for a statistically significant negative contemporaneous association between firm-specific volatility and the business cycle. That evidence may underestimate counter-cyclicality, since peaks that occur shortly before or after a recession tend to go against finding evidence for such a negative association although they may be economically related to the recession.

We therefore also analyze the dynamic interactions between firm-specific volatility and growth in real activity. While the impulse-responses for firm-specific sales volatility are at odds with the above-mentioned theories, the responses for earnings volatility do suggest that the key dynamics of both models are at play. In line with the implications of financial accelerator models, an increase in earnings volatility implies an increase in the credit spread and a decrease in real GDP. In line with the implications of irreversibility models, growth in GDP and investment initially declines, then increases somewhat above its initial level, which in the theory reflects pent-up investment and hiring being undertaken. However, the magnitude of the effects is very small.

Moreover, we find that firm-specific earnings volatility does not Granger-cause GDP growth or investment growth, and we find very little evidence for Granger-causality in the opposite direction, either in a bi-variate Vector Autoregression (VAR) or in a VAR that adds the credit spread. At a forecast horizon of 100 quarters, firm-specific earnings volatility explains about 5 percent of the fluctuations in real GDP growth and about 16 percent of the fluctuations in the credit spread. These shares are much smaller than those found by Christiano, Motto, and Rostagno (2013) where firm-specific volatility explains virtually the entire variance of the external finance premium and therefore have an important effect on aggregate investment and output.[9]

Our paper is structured as follows. Section 2 discusses sample selection and data treatment. Section 3 details our econometric approach for estimating changes in firm-specific volatility and compares it to common measures of firm-level volatility and dispersion. Section 4 presents our estimates of firm-specific volatility. Section 5 discusses the implications for volatility trends. Section 6 characterizes the contemporaneous relation between firm-specific volatility and the business cycle. Section 7 documents the dynamic relation between firm-specific volatility, credit spreads and the aggregate real economy. Section 8 concludes.

[9] In this sense, the present paper's findings are in between those of Christiano e.a. (2013) and those of Levin, Natalucci, and Zakrajsek (2004), who find in a financial accelerator model that changes in the external finance premium are not driven by firm-specific volatility, but by changes in the expected cost of default.

2 Data

This section discusses sample selection, cleaning, and the computation of growth rates.

We use quarterly data for publicly traded US firms from Compustat to compute firm-level growth rates in net sales and operating income after depreciation.[10] Our baseline results are based on nominal data, but in our penultimate section we report robustness to deflating sales and earnings by the Producer Price Index (PPI) at the 6-digit NAICS sector level, which we obtained from the Bureau of Labor Statistics.

We include only firms that are actively traded on a US stock exchange or actively trade securities on US over-the-counter markets.[11] We exclude firms that trade on US financial markets only through American Depositary Receipts (ADRs). We also exclude all other firms headquartered outside the United States.

Some firms in Compustat have changed the definition of their fiscal year of the course of data availability. This is reported as a change in the fiscal year end month. This causes double observations for the same firm. We avoid eliminating these firms altogether by keeping these firms' observations for the single-longest fiscal year definition.[12] This step was sufficient to eliminate double observations.

We only consider firms with fiscal years ending in March, June, September or December. Because of this, every fiscal quarter in our dataset perfectly corresponds to a single calendar

[10] Net sales equals gross sales minus cash discounts, trade discounts, and returned sales and allowances for which credit is given to the customer. We capture earnings by the variable operating income after depreciation. This is operating income minus the cost of goods sold, fixed costs and depreciation.

[11] We consider only firms for which the major exchange or over-the-counter market is listed in Compustat as: the New York Stock Exchange; NYSE Amex; OTC Bulletin Board; NASDAQ-NMS Stock Market; Midwest Exchange (Chicago); Pacific Exchange; Philadelphia Exchange; Other [exchanges]-OTC. Among others, we exclude subsidiaries, consolidated parents and non-traded companies.

[12] We determined the single-longest fiscal year definition based on the entire period of data availability in Compustat quarterly, i.e. 1961Q1-2012Q4. We completely drop firms that happen to have two fiscal year definitions which the firm used for an equal number of quarters and were in use longer than any other fiscal year definition.

quarter. This is important because our estimation procedure, which we detail in Section 3, yields a separate point estimate for firm volatility in any individual quarter. All the results in our paper are plotted with respect to calendar years and quarters.

We report results based on three growth rate measures. The first is the percentage change in any firm i's level of net sales S_{it} from quarter $t-4$ to quarter t:

$$\gamma_{it} = \frac{S_{it} - S_{i,t-4}}{S_{i,t-4}} * 100 \tag{1}$$

We call this the regular sales growth rate.[13] By measuring the change in sales with respect to its level four quarters before, we prevent seasonal fluctuations in the level of sales from influencing the growth rate.

Our second growth rate is a modified sales growth measure which is analogous to the annual growth rate in Davis, Haltiwanger, Jarmin, and Miranda (2006):

$$\widetilde{\gamma}_{it} = \frac{S_{it} - S_{i,t-4}}{(S_{i,t} \ + \ S_{i,t-4}) \ / \ 2} * 100. \tag{2}$$

We refer to this as the Davis-Haltiwanger (DH) growth rate. This measure is symmetric and bounded between -200 and 200. The advantage of that feature is that any increase in sales from a very low level to a very high level does not translate into an extreme growth rate which would drive all results.[14]

Our third growth rate is that for operating income. Operating income is frequently negative.

[13] We drop observations with negative net sales. Negative observations for net sales are plausibly genuine. However, including these observations would complicate the computation of growth rates, while the gain would be negligible since negative net sales account for a small fraction of observations.

[14] To achieve symmetry, DH sales growth is more negative for negative growth rates, but less positive for positive growth rates, than the regular growth rate. In Section 4, we will discuss how this difference affects measured firm-specific volatility. From (1) and (2), it follows that $\widetilde{\gamma}_{it} = \gamma_{it}\ [S_{i,t-4}/((S_{it} + S_{i,t-4})/2)]$. Assuming positive net sales S_{it} and $S_{i,t-4}$, for γ_{it}, $\widetilde{\gamma}_{it} > 0$ it holds that $[S_{i,t-4}/((S_{it} + S_{i,t-4})/2)] < 1$, while for γ_{it}, $\widetilde{\gamma}_{it} < 0$ it holds that $[S_{i,t-4}/((S_{it} + S_{i,t-4})/2)] > 1$. In both cases, this implies that $\widetilde{\gamma}_{it} < \gamma_{it}$. The third case is $\gamma_{it} = \widetilde{\gamma}_{it} = 0$. Therefore, it holds that $\widetilde{\gamma}_{it} \leq \gamma_{it}$ for positive net sales.

Therefore, we cannot compute the growth rate in analogy with equation (1). Doing so would yield meaningless results when operating income is negative in t and/or $t-4$. We compute growth in earnings based on the difference in operating income I_{it} in quarter t with respect to its level four quarters before, divided by the four-quarter lag of net sales:

$$\tilde{\tilde{\gamma}}_{it} = \frac{I_{it} - I_{i,t-4}}{S_{i,t-4}} * 100 \tag{3}$$

We do not compute a Davis-Haltiwanger style measure for earnings growth since such a measure would be more difficult to interpret. At any rate, it would not be bounded between -200 and 200.

We compute all growth rates for continuers only, i.e. we only compute a growth rate if all levels variables on the right-hand size are available and non-zero. Our dataset contains only publicly traded firms, which is not an appropriate sample for studying firm births and bankruptcies. It is likely that most firms that newly appear into Compustat already existed before, for instance as a privately held firm, such that assuming a zero level of sales or earnings in the quarter before they enter would overestimate their growth rate. Similarly, not all firms that disappear from Compustat are going into bankruptcy. They may merely be delisting or may be acquired by another firm.

At any rate, the sum of entry and exit rates is relatively stable over the course of our sample (1978Q1-2012Q4), so accounting for entry and exit would likely increase the level of measured volatility without materially affecting the volatility patterns. Another issue is that entry and exit change the composition of firms. For instance, listing appears to be pro-cyclical, and these may the more volatile firms, while these more volatile firms may delist during recessions. This would tend to make measured volatility pro-cyclical. However, our estimation procedure controls for changes in composition.

Next, we drop observations which appear to be associated with firm mergers and splits. To this end, we construct a proxy variable which indicates a merger at time t when the lowest value of a firm's quarterly nominal sales in quarters t through $t+3$ is more than double the highest value of that firm's sales in quarters $t-1$ through $t-4$. Analogously, we consider that a split occurred at time t when the highest value of a firm's sales in quarter t through $t+3$ is less than half the lowest value of that firm's sales in quarters $t-1$ through $t-4$. In both cases, we drop all growth rates for that firm for the period t through $t+3$, because these growth rates would be affected by the merger or split. We treat observations before and after the split or merger as belonging to different firms.

We also drop observations in Compustat quarterly which appear to assign an annual sales or earnings figure to a single quarter. Suspected annual observations occur when the level of net sales is only recorded every four quarters initially, usually in the fourth fiscal quarter, after which sales is recorded every quarter, and this change in recording frequency is coincident with an unusually large drop in the recorded level of sales. To account for annual observations which occur right before quarterly data, we drop a time-t observation when the firm is active in t but was inactive in all three preceding quarters, and where the recorded level of sales in t exceeds twice the maximum of sales in quarters t through $t+4$. For this purpose, we consider a firm as inactive when either the firm is not in Compustat at that time, or when the firm is in Compustat but both the level of sales and earnings are unavailable or zero. To omit other annual observations, we also drop time-t observations if the firm is active at t but is inactive in quarters $t-3$ through $t-1$ and $t+1$ to $t+3$.

While levels data are available in Compustat quarterly from 1961Q1 onwards, we perform analysis on growth rates for the time period 1978q1-2012q4. Earlier years have a substantially smaller number of observations in Compustat quarterly, as the share of publicly traded firms covered by Compustat appears to have increased over time.[15]

To ensure that our volatility estimates capture the central tendency of the data and are not driven by a small number of observations, we drop the tails of the sector-level sales and earnings growth distribution for the regular growth rates (1) and (3). In particular, we drop five percent of observations on either end of the growth rate distribution over the entire time period within 3-digit NAICS sectors for manufacturing firms and within 2-digit NAICS sectors for all other firms. This step is important: without it, our measure spikes upwards whenever there is one extreme growth rate. The same holds true for the cross-sectional standard deviation. The reason we can compute these measures is precisely that we cut the tails.

We do not drop tail observations for the DH growth rate (2). This measure is bounded, so there are no extreme growth rates. This is another approach that allows us to computeg our measure of firm-specific volatility and cross-sectional standard deviations.

The regular and DH growth rates can be seen as different weighting schemes, with tail observation having a tempered effect in the DH growth rate and being dropped altogether for the regular growth rates. Any result will be more robust if it holds across these two growth rates.

After this step, we only include observations for (1) and (3) for which both growth rates are in the dataset. This ensures a common sample for regular sales and earnings growth rates.

We excluding utilities firms since this sector is regulated, and we exclude finance and insurance firms since these financial companies would likely behave very differently than the other firms in Compustat. In addition, one goal of our paper is to gauge the effect of firm volatility on credit

[15] In Compustat quarterly without any cleaning apart from keeping the single-longest fiscal year definition so that there are no double observations, the number of US firms for which we could compute a sales growth rate is only 494 in 1963Q1, and has risen to 2,634 for 1978Q1. Coverage appears to be virtually complete only from about 1983Q1, when 5,342 firms are in Compustat. We include the period 1978Q1-1982Q4 in our sample to capture the two recessions of the early 1980s. At any rate, our estimation technique controls for changes in sample composition.

spreads, which we believe to be able to do most cleanly if we only consider non-financial firms.

Finally, we only consider sectors which have a large enough amount of firms in most quarters. This is necessary because our estimator of firm-specific volatility relies on sector-level estimations.

Table 1 contains the list of 2-digit NAICS sectors we use, and Table 2 contains the list of 3-digit NAICS sectors within manufacturing that we use. Each table provides the total number of observations for the regular sales growth rate (1) and earnings growth rate (3) in our cleaned sample 1978q1-2012q4, after dropping five percent of observations in each tail of the sector-level growth distribution. The table also provides the average quarterly number of observations by sector.

After splitting up firms to account for mergers and splits, our sample consists of 353,931 observations for 11,565 firms for regular sales growth and earnings growth. About half of these observations are for manufacturing firms. For the DH growth rate, the sample consists of 426,754 observations for 12,730 firms.

Tables 1 and 2 also provide the average number of firms by quarter in each sector. For non-manufacturing sectors, the average number of firms ranges from 49 in construction to 311 in information. For manufacturing firms, the average ranges from 20 in petroleum to 384 in computer and electronic product manufacturing.

Figure 1 plots the distribution of our four growth rate measures for our cleaned Compustat sample. Solid black lines are medians, dashed lines 25th and 75th percentiles, and the solid red line is the mean growth rate in every quarter. Shaded areas are NBER recessions. The top row pertains to sales growth, the left to regular sales growth and the right to DH sales growth. The bottom graph pertains to earnings growth. Sales growth accurately indicates slowdowns in all recessions in the sample. Earnings growth slows down in most recessions, but this slowing tends to be much more muted except in the recessions of 1981-1982 and 2001.

3 Estimation

This section describes our procedure for estimating cyclical changes in firm-specific volatility, and compares it to common measures of firm-level volatility and dispersion.

3.1 Our Method

Our volatility measure is based on the residuals of regressions of the following form:

$$\gamma_{it} \;=\; c \;+\; a_i \;+\; b_t \;+\; e_{dt} \;+\; \varepsilon_{it} \tag{4}$$

All regressions in this paper are for 1978Q1-2012Q4. We obtain the residuals ε_{it} from separate regressions of equation (4) by 3-digit NAICS sector for manufacturing firms, and by 2-digit NAICS sector for sectors other than manufacturing.

γ_{it} represents net sales growth or earnings growth for firm i as defined in equations (1) through (2). The constant is c. We include firm fixed effects a_i, time effects b_t, and firm size effects e_{dt}.[16]

We estimate the firm size effects e_{dt} using dummy variables that indicate whether a firm belongs to a particular decile in the distribution of sales-to-GDP ratios for the relevant sector over the sample period. The size deciles are based on the distribution of sales-to-GDP ratios over precisely the same sample for which we regress equation (4).[17] To ensure that the sales-to-GDP ratios do not reflect seasonal factors, we compute the ratios based on four-quarter sums of sales and GDP. In particular, we construct the sales-to-GDP ratio for firm i in quarter t as the ratio of the sum of quarterly nominal sales in $t-3$ through t to the sum of quarterly nominal GDP in

[16] We estimate equation (4) and all other fixed effects regressions in this paper using the Stata within-estimator `xtreg, fe`.

[17] This also means that we compute sales-to-GDP deciles separately depending on whether γ_{it} in regression (4) stands for regular sales growth or earnings growth on the one hand, or DH sales growth on the other hand.

$t-3$ through t.

Tables 1 and 2 not only list the sectors we use along with the available observations by sector, but also state the median sales-to-GDP ratio by sector. Firm size varies substantially across sectors. In this respect, note that our definition of size effects captures within-sector variation in firm size, such that the sectoral growth rate b_t and the size effect e_{dt} capture independent information.

In equation (4), the residuals ε_{it} capture the extent to which a firm's growth in a quarter is atypical given the firm's typical growth rate a_i over the estimation period, the typical growth rate b_t in the firm's sector at time t, and given the firm's size at time t relative to the typical distribution of firm size in its sector.[18]

We estimate the standard deviation of the residual from equation (4) by a term proportional to the absolute value of the estimated residual $\widehat{\varepsilon}_{it}$:

$$\widehat{\sigma}_{\varepsilon,it} = \sqrt{\frac{\pi}{2}}\ |\widehat{\varepsilon}_{it}| \tag{5}$$

Therefore, we estimate every firm i's volatility in any quarter t from a single value of the residual. If the true error term ε_{it} is normally distributed with mean 0, i.e. $\varepsilon_{it} \sim N(0, \sigma^2_{\varepsilon,it})$, equation (5) yields an unbiased estimator $\widehat{\sigma}_{\varepsilon,it}$ of the true standard deviation $\sigma_{\varepsilon,it}$.[19]

We translate the estimated values for firm-specific volatility $\widehat{\sigma}_{\varepsilon,it}$ into an aggregated measure for every quarter t by means of regressions of the following form:

[18] We use heteroskedasticity-robust standard errors throughout this paper. As the results in Section 4 reveal, the typical standard deviation of ε_{it} changes substantially over time, indicating that it is important to account for heteroskedasticity.

[19] Taking expectations of equation (5), but assuming that we know the true error term ε_{it}, we obtain: $E(\widehat{\sigma}_{\varepsilon,it}) = \sqrt{\pi/2}\ E(|\varepsilon_{it}|)$. If ε_{it} is normally distributed with mean 0 and variance $\sigma^2_{\varepsilon,it}$, then $|\varepsilon_{it}|$ is half-normally distributed with $E(|\varepsilon_{it}|) = \sqrt{2/\pi}\ \sigma_{\varepsilon,it}$. Therefore, $E(\widehat{\sigma}_{\varepsilon,it}) = \sigma_{\varepsilon,it}$, i.e. the estimator $\widehat{\sigma}_{\varepsilon,it}$ is unbiased. Equation (5) is the firm-level equivalent of McConnell and Perez-Quiros's (2000) formula for the volatility of aggregate output growth.

$$\widehat{\sigma}_{\varepsilon,it} \;=\; \kappa \;+\; \alpha_i \;+\; \beta_t \;\;+\; \nu_{it} \tag{6}$$

The time fixed effect β_t captures the typical level of firm-specific volatility in quarter t, controlling for firm fixed effects α_i . The error term is ν_{it}.

We run regression (6) for the entire economy, for every 2-digit NAICS sector as well as for every 3-digit sector within manufacturing. For any manufacturing firm in any of these regressions, the dependent variable reflects volatility in firm growth rates that is atypical relative to growth in the firm's 3-digit sector. For any non-manufacturing firm, $\widehat{\sigma}_{\varepsilon,it}$ reflects volatility that is atypical relative to the firm's 2-digit sector.

In Section 4, we will plot the time-path of β_t to uncover the evolution in firm-specific volatility.[20] Because of the inclusion of firm fixed effects α_i, this estimate controls for changes in the composition of firms. This is important because evidence by Fama and French (2004), Davis, Haltiwanger, Jarmin, and Miranda (2006) and Brown and Kapadia (2007) suggest that riskier firms have become more likely to list on the stock market.[21] Because such changes in sample composition do not reflect changes in the composition of the overall population of firms, we control for them.

Controlling for changes in sample composition is also important because the extent of Compustat coverage of publicly traded firms may well have changed even over the course of our sample period, which starts in 1978Q1. In particular, a substantial number of Nasdaq and over-the-

[20] More precisely, we plot the sum of the time effect and the constant that is reported in the Stata within-regression `xtreg,fe`. The constant in `xtreg,fe` correctly represents firm volatility in the first quarter of the sample, after averaging out firm effects.

[21] Davis, Haltiwanger, Jarmin, and Miranda (2006) find that most of the trend increase in the rolling ten-year standard deviation of employment growth of publicly traded firms is due to firms newly listed in the 1980s and 1990s being much more volatile than earlier cohorts. Fama and French (2004) and Brown and Kapadia (2007) find that the trend increase in firm-specific stock return volatility can be largely attributed to new listings by risky companies.

counter firms newly appears in Compustat quarterly in 1981 and 1982, while these firms were virtually absent from the database before. From 1983Q1 onwards, Compustat coverage appears to have been fairly comprehensive.

3.2 Relation to Other Common Dispersion and Volatility Measures

We now discuss the relation of our measure to common measures for dispersion and firm volatility.

First, we argue that ours is a better measure of firm-specific volatility than measures of dispersion in the distribution of firm growth rates. To this point, we first show how the cross-sectional standard deviation is related to our measure, and then discuss how the differences between the two measures help ours to better capture firm-specific volatility. In this context, the interquartile range has similar drawbacks as the cross-sectional standard deviation, so we argue that our measure improves on both of the two common dispersion measures.

To see that the cross-sectional standard deviation is related to our measure of firm volatility, consider the following estimation model which is a variant of that in equations (4) through (6). Consider running the following regression by sector:

$$\gamma_{it} \;=\; b_t \;+\; \varepsilon_{it} \tag{7}$$

In this case, $\widehat{b}_t = \overline{\gamma}_t$, the cross-sectional average at time t of the firm-level growth rates γ_{it}. Therefore, the residual $\varepsilon_{it} = \gamma_{it} - \overline{\gamma}_t$.

Then estimate the variance of the residual ε_{it} by its square:

$$(\widehat{\sigma}_{\varepsilon,it})^2 \;=\; (\widehat{\varepsilon}_{it})^2 \tag{8}$$

and regress that estimate of the variance on time effects by sector:

$$(\widehat{\sigma}_{\varepsilon,it})^2 \;=\; \beta_t \;+\; \nu_{it} \tag{9}$$

In equation (9), $\widehat{\beta}_t$ is the cross-sectional average of the squared residuals from equation (7). That is to say, $\widehat{\beta}_t = (1/N)\sum_{i=1}^{N}(\gamma_{it}-\overline{\gamma}_t)^2$, with N the number of firms in the sample used to regress equation (9). This implies:

$$\sqrt{\frac{N}{N-1}\ \widehat{\beta}_t} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(\gamma_{it}-\overline{\gamma}_t)^2} \tag{10}$$

Therefore, using equations (7) through (10) to obtain $\sqrt{[N/(N-1)]\ \widehat{\beta}_t}$ is equivalent to computing cross-sectional standard deviations by sector.

We argue that the estimator in equations (4) through (6) is a better measure of firm-specific volatility than the cross-sectional standard deviation. The cross-sectional standard deviation reflects any reason for dispersion in the cross-sectional distribution of growth rates, whether it reflects firm-specific shocks or a different response to common shocks. It also does not control for changes in sample composition. First, dispersion can increase if firms that newly list happen to be more different in terms of trend growth than is the case for firms that were previously listed. Second, dispersion can also increase when firms that newly list are instrinsically more volatile.

Equation (4) controls for the possibility that firms in different sectors and of different sizes react differently to common shocks. In some cases researchers have computed cross-sectional standard deviations by sector. In principle, it would be possible to do so by sector-size category, which would achieve a similar result as our controlling for time-varying sector and size effects in equation (4). Equation (4) also controls for the first above-mentioned aspect of changes in sample composition in that it controls for the typical growth rate of a firm. Equation (6) controls for the second aspect of changes in sample composition in that it controls for the typical level of volatility of a firm.

Secondly, our estimator is different in spirit from rolling standard deviations, which is the measure that earlier papers have used to estimate time-variation in firm-level sales growth volatility in the United States. Comin and Philippon (2005), Comin and Mulani (2006) and Davis, Haltiwanger, Jarmin, and Miranda (2006) compute the volatility of firm i in year t from the centered ten-year standard deviation of firm-level growth rates:

$$\sigma^r_{it} = \sqrt{\frac{1}{10}\sum_{\tau=-4}^{\tau=5}(\gamma_{i,t+\tau} - \overline{\gamma}_{it})^2} \tag{11}$$

where $\gamma_{i,t}$ represents sales or employment growth between year $t-1$ and t for firm i. $\overline{\gamma}_{it}$ captures the firm's average growth between $t-4$ and $t+5$. All three papers use annual data and do not adopt a degrees-of-freedom correction. Their measure of typical firm-level volatility in any year t is the cross-sectional mean or median of σ^r_{it} .

While equation (11) assigns the volatility estimate to year t, σ^r_{it} really does not yield a separate estimate of volatility for any year, but captures average volatility for a ten-year period.

By computing an aggregated measure based on equation (11) for distinct ten-year periods, one can gauge longer-run changes in firm-level volatility. However, this measure is not designed to capture fluctuations within a ten-year period. This is because rolling equation (11) forward implies overlapping windows which smooth out short-run fluctuations. Adopting the common definition of the business cycle as a cycle that takes between six quarters and eight years to complete,[22] this implies that a rolling volatility measure is not designed to indicate cyclical changes in firm volatility.

Because of these issues, the rolling standard deviation cannot serve to draw conclusions about the precise timing of changes in volatility.

Another disadvantage of the rolling standard deviation is that it captures all changes in firm-

[22] See Stock and Watson (1999).

level variables, whether these are due to firm-specific events or other conditions such as macroeconomic or sector-wide shocks. It also captures changes in firm growth rates irrespective of whether the changes were predictable or even planned by the firm.

A major advantage of our measure is that our estimator $\widehat{\beta}_t$ from equation (6) captures volatility in a given quarter, such that our measure captures both cyclical and longer-run fluctuations in firm volatility. It allows us to draw precise implications about the timing of changes in firm volatility, which allows us to test theories where firm-specific volatility has a dynamic effect on the macroeconomy. Another advantage is that it captures firm-specific volatility because we regress equation (4) by sector and include time and size effects. Because equation (4) includes some likely determinants of firm growth rates, a smaller share of the variation in the residuals should be predictable.

4 Estimated Firm-Specific Volatility

In this section, we present graphs with our estimates of firm-specific volatility. In the next section, we will discuss the implications for volatility trends while in the subsequent two sections we will discuss the cyclical properties of firm volatility and its relation to credit spreads.

4.1 Medium-Run Patterns in Firm Volatility

Figure 2 shows firm-specific volatility along with a 95 percent confidence interval, estimated from equations (4) through (6). Firm-specific volatility for all firms in our cleaned Compustat sample is in the top row while firm volatility for the manufacturing sector is in the bottom row. From left to right, the columns pertain to firm volatility in regular sales growth (1), volatility in Davis-Haltiwanger (DH) sales growth (2), and volatility in earnings growth (3). Shaded areas indicate NBER recessions.

In Figure 2, the level of firm volatility in any quarter indicates the size of a one-standard deviation percentage change in sales or earnings with respect to four quarters before.

Note that the levels of volatility cannot be compared across variables because the definitions of the growth rates are not equivalent across variables, and because we omit tails of the distribution for regular and earnings growth rates but not so for DH sales growth rates.[23] In Sections 6 and 7, we will specify firm volatility in percentage deviations from trend, a measure where the magnitudes are comparable across variables.

The top row of Figure 2 reveals that there are fairly clear-cut turning points between periods with increasing and decreasing volatility. These turning points are similar across the three variables, and tend to occur around the time of recessions. Firm volatility increases during the two recessions of the early 1980s, peaking in 1983Q4, which is four quarters after the end of the 1981-1982 recession. It then decreases through about 1991Q3, which is two quarters after the end of the 1990-1991 recession. It then increases through about 2001Q4, which is the last quarter of the 2001 recession. It then decreases through the end of the sample period, with some signs of a temporary increase during the 2007-2009 recession.

Note that we were only able to obtain these precise estimates on the timing of turning points in firm volatility because our technique yields separate estimates of firm volatility for every quarter. Conclusions on the precise timing would not be possible with rolling standard deviations.

The top right panel of Figure 2 reveals a pronounced seasonal pattern in earnings volatility,

[23]Earnings growth volatility appears to be always below volatility in both sales growth measures. However, recall from equation (3) that we compute earnings growth with lagged sales in the denominator. In absolute value, sales is often larger than earnings. The comparatively large absolute values of sales tend to imply comparatively small absolute values for the growth rate in equation (3), and therefore tend to imply low values for measured earnings volatility. As for the comparison between regular sales growth and DH sales growth, the fact that we omit tail observations for the former but not for the latter likely accounts for measured DH sales growth volatility always being below measured regular sales growth volatility in Figure 2. The difference in definition itself has ambiguous consequences on the level of volatility. This is because DH sales growth is more negative for negative growth rates, but less positive for positive growth rates, as a footnote in Section 2 shows.

while there is no apparent seasonality in sales volatility. Since seasonal fluctuations in firm volatility should not bear any relationship to seasonally adjusted measures for growth in real activity, our results in Sections 6 and 7 are based on seasonally adjusted firm-specific volatility.

The bottom row of Figure 2 documents that results for the manufacturing sector are similar. In this respect, note that manufacturing accounts for 49 percent of observations in our full sample. Two noteworthy differences are that for regular sales growth, there is a more pronounced increase in firm volatility after the NBER-dated recession of 2007-2009 than in the whole economy, and that earnings volatility of manufacturing firms continues to decline through the late 1990s.

At this stage, we do not have an economic explanation for our finding that turning points in firm volatility coincide with recessions. Because we control for firm fixed effects in the second-stage regression, changes in our measure of firm volatility cannot be due to changes in the sectoral composition of the sample. Therefore, they cannot reflect changes in the share of sectors with high degrees of turnover. Possibly, firms' attitude to risk changes as a result of the extent to which risk materializes. The recessions of the early 1980s and the 1987 stock market crash may have contributed to firms taking less risk, resulting in a decrease in realized firm volatility. During the productivity acceleration of the second half of the 1990s, firms may have placed lower subjective probabilities on adverse outcomes, and therefore may have taken more risk, with firm volatility increasing as a result. Firm volatility declined sharply after the 2001 recession, so there may have been something special about this recession which raised firms' subjective probabilities of a negative event.

4.2 Robustness: Real Growth Rates

Firm-specific volatility in Figure 2 is based on nominal sales and earnings growth. Because of that, it is in principle possible that differences in price changes across narrow industries affect our estimates of firm volatility. For instance, when prices in a 6-digit NAICS sector increase relative to other 6-digit sectors in the same 2-digit sector or in the same 3-digit manufacturing sector, this tends to increase the nominal sales of firms in that 6-digit sector relative to average in the broader sector. This could affect our estimates of firm-specific volatility even if quantities produced did not change.

We therefore check for robustness with respect to deflating nominal sales and earnings for every firm by the Producer Price Index (PPI) specific to the 6-digit NAICS sector to which the firm belongs. We use a subset of cleaned Compustat sample for which data on 6-digit PPIs are available. Among those observations, we dropped sectors for which there was an insufficient number of firms left: all non-manufacturing sectors as well as three of the 3-digit manufacturing sectors listed in Table 2.[24] For similar reasons, we restrict the sample to 1986Q1-2012Q4 for this purpose.

The red lines in Figure 3 indicate firms-specific volatility estimated using equations (4) through (6) on these real sales and earnings data. The black lines indicate firm-specific volatility based on nominal growth rates when restricting the sample to the same firm-quarter cells.

Figure 3 reveals that for the restricted manufacturing sector, firm-specific volatility in real sales and earnings growth rates is virtually identical to firm-specific volatility in nominal growth rates. Graphs comparing real and nominal firm-specific volatility by 3-digit manufacturing sector have the same implication. These results suggest that differences in price changes across sectors do not have a material effect on our estimates of firm-specific volatility. We use nominal sales and earnings growth in the remainder of the paper.

[24] Industry-level PPI data are from the Bureau of Labor Statistics. We drop all firms in the joint sector 313 Textile mills, 314 Textile product mills and 315 Apparel manufacturing, as well as all firms in the sectors 322 Paper manufacturing and 326 Plastics and rubber products manufacturing.

5 Trends in Firm Volatility

In this section, we document the implications of our estimates for trend changes in firm volatility.

Evidence to date on US firm-level volatility is provided by Comin and Philippon (2005), Comin and Mulani (2006) and Davis, Haltiwanger, Jarmin, and Miranda (2006). These studies all use rolling ten-year standard deviations on annual data. They all document a trend increase in the volatility of publicly listed firms, with Davis e.a. (2006) showing that the increase in firm volatility is much less pronounced once they control for the time of first listing by means of cohort effects.

The bold line in Figure 4 replicates this finding by computing centered forty-quarter rolling standard deviations on our cleaned Compustat sample. We compute the rolling standard deviation σ_t^{roll} assigned to quarter t as the cross-sectional average of firm-level rolling standard deviations σ_{it}^{roll}

$$\sigma_t^{roll} = \frac{1}{N_t} \sum_{i=1}^{N_t} \sigma_{it}^{roll} \tag{12}$$

where N_t is the number of firms for which a rolling standard deviation exists in quarter t, and where the forty-quarter firm-level rolling standard deviation σ_{it}^{roll} is:

$$\sigma_{it}^{roll} = \sqrt{\frac{1}{39} \sum_{\tau=-19}^{\tau=20} (\gamma_{i,t+\tau} - \overline{\gamma}_{it})^2} \tag{13}$$

where $\overline{\gamma}_{it} = \frac{1}{40} \sum_{\tau=-19}^{\tau=20} \gamma_{i,t+\tau}$. The division through 39 in equation (13) reflects a degrees-of-freedom correction.

Since computing a forty-quarter standard deviation requires that a growth rate be available for forty consecutive quarters, the samples are based on fewer observations than in our full sample: 269,773 observations for 3,731 firms in the case of Davis-Haltiwanger growth rates, and 130,303 observations for 1,937 firms in the case of regular sales and earnings growth rates. Recall that we drop tail observations for the latter two growth rates, which implies substantially fewer periods with forty or more consecutive quarters of observations.

In computing rolling standard deviations, we do not control in any way for changes in sample composition. Figure 4 reveals a gradual increase in the rolling standard deviation for most of the sample. For regular sales growth, the standard deviation increases from 14.33 to 17.18, an increase of 19.83 percent, from the beginning of the sample[25] to the window 1997Q2-2007Q1 (centered in 2002Q1). For Davis-Haltiwanger sales growth, the increase over the same time frame is 26.15 percent, while for earnings growth it is 51.28 percent.

These percent increases are on the same order of magnitude as the increase in ten-year rolling standard deviations of employment growth rates for publicly listed firms reported by Davis e.a. (2006).[26]

Interestingly, the upward trend in sales volatility for publicly traded firms seems to have been reversed after the sample used by Davis e.a. (2006). In fact, their sample ended shortly before the peak. On the other hand, earnings volatility stayed fairly stable after the window centered in 2002Q1.

We now return to our own estimates of firm-specific volatility, graphed in the top row of Figure 2. We do not find any evidence for a trend increase in firm-specific volatility over the period 1978Q1-2012Q4. On the contrary, firm-specific volatility is substantially lower at the end of the sample than in the beginning. Firms are less volatile in 2012 than at any other time in the sample. From 1978Q1 to 2012Q4, firm-specific volatility drops by 29.39 percent in the case of regular sales growth, by 14.70 percent for Davis-Haltiwanger sales growth, and by 16.01 percent

[25] This is the time window 1978Q1-1987Q4, which is centered in 1982Q4.

[26] The solid line in Figure 3 of Davis e.a. (2006) reports the increase in the unweighted ten-year rolling standard deviation in employment growth rates for publicly traded Compustat firms, with employment growth computed using a formula analogous to our equation (2). The rolling standard deviation centered in 1982 is about 17 while it is about 22 for Davis e.a.'s (2006) most recent window, centered in 2001. This is an increase of 29.41 percent.

for earnings growth. Note that these estimates control for changes in sample composition through the inclusion of firm fixed effects in the growth rate regression (4) as well as in the volatility regression (6).

These results suggest that the 2007-2009 recession did not halt the Great Moderation as far as firm-level sales and earnings growth is concerned. Considering only trend changes in volatility, there appear to have been structural changes in the economy that have caused firms to become more stable.

Figure 4 reconciles our findings with earlier findings of a trend increase in the volatility of publicly traded firms. The thin solid line in that figure plots our estimates of firm-specific volatility using an estimation model which is that of equations (4) through (6) except for the fact that we now omit firm fixed effects from the volatility equation (6). Therefore, this measure does not control for the effect of changes in sample composition on firm volatility, a feature which it shares with rolling standard deviations. To further enhance comparability, we computed this measure using only observations that are part of a continuous spell of at least forty available growth rate observations.

The long dashed lines in Figure 4 are centered forty-quarter rolling averages of this quarterly measure of firm-specific volatility, where the value assigned to quarter t is the average of firm volatility between $t - 19$ and $t + 20$. These rolling averages of firm-specific volatility serve for comparison with the rolling standard deviations.

Like the rolling standard deviations, the rolling averages of quarterly firm-specific volatility gradually increase for much of the sample. In this case, the upward trend is reversed for all three variables, and the peaks occur somewhat earlier than for the rolling standard deviations. For instance, for regular sales growth, the peak occurs in the window 1993Q2-2003Q1 (centered in

1998Q1). From the beginning of the sample until that window, volatility increases by 24 percent for regular sales growth. Over the same timeframe, volatility increases by 25.14 percent for Davis-Haltiwanger sales growth, and by 49.76 percent for earnings growth.

Therefore, our method implies similar trend changes in volatility when we do not control for changes in sample composition. Therefore, our technique can easily replicate the finding of a trend increase in firm volatility. It suffices to drop the firm fixed effects from the second-stage regression. Recall from Figure 2 that when we do include a firm fixed effect, this result is completely overturned.[27]

This is strong evidence in favor of the hypothesis that the trend increase in firm-level volatility documented by earlier studies is due to changes in sample composition. Comin and Philippon (2005), Comin and Mulani (2006) and Davis e.a. (2006) do attempt to control for changes in sample composition by regressing rolling standard deviations on firm characteristics such as firm size and age, and Comin and Mulani (2006) regress rolling standard deviations on firm fixed effects. In all their reported cases, firm volatility for publicly traded firms shows a trend increase.

It is not clear why controlling for fixed effects completely overturns the finding of a trend increase in quarterly firm-specific volatility of publicly traded firms while it does not seem to have such a large effect for rolling standard deviations.

The above finding shows how important it is to control for changes in sample composition. While changes in listing criteria are a first reason for this, a second reason is that Compustat coverage of publicly traded firms has expanded over time. From about 1983, coverage appears to have been fairly comprehensive, but not so in earlier years. A substantial number of Nasdaq

[27] The same is true when we estimate firm-specific volatility with a firm fixed effect in the second stage on the sample appropriate for comparison with rolling standard deviations. When we estimate the model excluding the second-stage fixed effect on our full sample, we find a trend increase. These results are available from the authors.

and over-the-counter firms newly appears in Compustat in 1981 and 1982, while these firms are virtually absent from the database in earlier years.

Estimating a model without firm fixed effects in the second stage on our full sample (unreported here), we find pronounced and sudden increases in firm-specific volatility in 1981 and 1982, which is very likely to reflect the inclusion of more volatile firms from that time onwards. For the sample used to compute rolling standard deviations, this effect will be spread out over time because of the requirement of forty consecutive quarters of observations. As Figure 4 shows, a sharp volatility increase is still visible at that time in the case of DH sales growth, and a pronounced increase in the rolling standard deviations for DH sales growth and earnings growth are still visible about five years later, when the centered forty-quarter standard deviation can be computed for the first time for some of these newly included firms. Our interpretation is that these sharp increases merely reflect the inclusion of the above-mentioned set of volatile firms, and that while no drastic increases are visible in later quarters, subsequent changes in the rolling standard deviation are affected by the spread-out effect of this inclusion.

To conclude, this section provides strong evidence that any earlier finding of a trend increase in firm volatility merely reflects changes in sample composition. There is no upward trend in the volatility of individual publicly traded firms once we control for changes in sample composition.

6 Firm Volatility and the Business Cycle

This section documents the contemporaneous relation of firm volatility with the business cycle, and relates our findings to those of earlier studies with firm dispersion.

6.1 Cyclical Properties of Firm-Specific Volatility

Since trends in firm-specific volatility are likely related to structural changes, not controlling for trends could bias our results. For instance, the fact that the Great Recession is at the end of the sample at a time when trend volatility is low could bias our results towards finding a positive relation between firm volatility and the business cycle. Therefore, we analyze the cyclical properties of deviations in firm-specific volatility from trend.

Figure 5 plots firm-specific volatility after seasonal adjustment,[28] along with the Hodrick-Prescott (HP) trends of these series with smoothing parameter 16,000. Because we use a relatively rigid filter, volatility can stay above trend for several years. This is what we need in order to translate high-volatility episodes into times with high de-trended volatility.[29]

The top panel of Figure 6 shows the implied de-trended series in percentage deviations from trend. De-trended firm-specific volatility in regular sales growth peaks during the recessions of 1980, 1990-91 and 2007-09, at levels between two and six percent above trend. Four quarters after the 2007-09 recession, volatility peaks at about ten percent above trend. It increases during the 1981-1982 recession, peaking four quarters after the end of the recession. It peaks four quarters before the beginning of the 2001 recession. Its three largest peaks -between ten and twelve percent above trend- do not occur during recessions, but four quarters after a recession (1981-82, 2007-09) or four quarters before a recession (2001). Volatility also increases about eight percent above

[28] We used multiplicative X12 seasonal adjustment. Recall the pronounced seasonal pattern in earnings volatility in Figure 2. We seasonally adjusted earnings volatility because seasonal patterns should not bear any relationship to growth in seasonally adjusted real activity measures. To treat all series in the same fashion, we seasonally adjust not only volatility in earnings, but also volatility in regular and DH sales growth. In the latter two cases, seasonal adjustment makes a relatively small difference.

[29] The reported results for regressions on recession indicators and correlations with GDP growth are robust to using a smoothing parameter at the more common setting of 1,600. In a VAR application on monthly data to gauge the effect of (macro) uncertainty on the economy, Bloom (2009) uses a baseline setting of 129,600 for HP filtering aggregate stock market volatility and other macroeconomic variables, as compared with the common setting of 14,400 for monthly data.

trend in 1987Q1, predating the stock market crash of 1987Q4 by three quarters.

De-trended volatility in Davis-Haltiwanger (DH) sales growth peaks during the recessions of 1980, 1990-91, 2001 and 2007-09, reaching about fifteen percent above trend in the recessions of the 2000s but peaking at less than two percent above trend in the 1980 and 1990-91 recessions. It increases during the 1981-82 recession and peaks one quarter after the end of the recession at eleven percent. Volatility also increases about nine percent above trend in 1986Q3.

Volatility in earnings growth peaks at levels between thirteen and sixteen percent above trend in the recessions of 2001 and 2007-09. It peaks two percent above trend at the outset of the 1980 recession. It increases from the 1981-82 recession onwards, and peaks at about eight percent above trend four quarters after the recession. It actually decreases during the 1990-1991 recession. Volatility also increases about seven percent above trend in 1987Q1.

This graph suggests that firm-specific volatility tends to peak during or around the time of recessions. De-trended volatility is particularly high before and during the 2001 recession and during and after the NBER-dated 2007-09 recession. It also reaches a substantial peak after the 1981 recession. In most cases, small and short-lived increases in de-trended volatility occur in the two other remaining recessions in the sample: 1980 and 1990-91.

In the remainder of this section, we produce two types of evidence to document the cyclical properties of firm-specific volatility. This analysis is similar to that of Bloom e.a. (2012) for the interquartile range, and is meant to allow us to draw comparisons with their work. Regressions of firm-specific volatility on a recession indicator constitute the first type of evidence, while correlations with GDP growth constitute the second. As we will discuss, these tests merely indicate the contemporaneous association between firm volatility and the business cycle. In the next section, we will test for the dynamic relation between these variables.

The top left part of Table 3 shows the results of regressing de-trended firm-specific volatility on a constant and a recession indicator which equals one if the economy is in recession according to the NBER business cycle reference dates and zero otherwise. We use Newey-West standard errors to correct for substantial serial correlation in the residuals as well as to correct for any heteroskedasticity.

The results imply that firm-specific volatility in regular sales growth is on average 0.08 percent below trend if the economy is not in recession, and is on average 0.15 percent above trend in a recession. The difference of 0.23 percent is not statistically significant. Firm volatility in DH sales growth is on average 0.65 percent below trend when the economy is not in recession and 2.88 percent above trend during recession. The difference of 3.53 percent is larger but is still not statistically significant at the 5 percent level. Firm volatility in earnings growth is 0.67 percent below trend when the economy is not in recession and 3.67 percent above trend when it is, with a difference of 3 percent that is not statistically significant.

These results reveal that de-trended volatility in DH sales growth and earnings growth are moderately higher during recessions than at other times, but the difference is not statistically significant. Volatility in regular sales growth is not materially higher during recessions.

Recall from the graphical analysis that volatility often peaks several quarters before or after NBER recessions. High volatility around the time of recessions is plausibly economically related to those recessions. However, the high levels of volatility at times relatively close to but outside of recessions tend to increase measured volatility at non-recession dates, and therefore tend to narrow the difference between volatility in recessions and other times. Therefore, the regressions in Table 3 may understate the case for counter-cyclicality.

The R-squareds from these regressions are very low, which indicates that recessions themselves explain a very small fraction of fluctuations in de-trended firm volatility. Any other determinants of firm volatility are omitted from the regressions and induce omitted variable bias to the extent that these variables are themselves correlated with the business cycle. Therefore, the results in Table 3 are indicative but not sufficient in themselves to make a definitive conclusion about cyclicality.

The bottom left part of Table 3 shows the results for the manufacturing sector. These results are similar. In this case, volatility in regular sales growth is actually somewhat lower during recessions, but the difference is again not statistically significant.

The top right part of Table 3 shows the correlations of de-trended firm-specific volatility for the whole economy with real GDP growth. The column labeled "gdpg1" pertains to annualized quarterly GDP growth while the column labeled "gdpg4" pertains to four-quarter GDP growth. Annualized quarterly GDP growth is a common measure of growth in real activity, while the four-quarter growth rates are in analogy with the fact that our firm-specific volatility measures are based on four-quarter firm-level growth rates.

The correlation with annualized quarterly GDP growth is small and statistically insignificant for all three variables. The correlation with four-quarter GDP growth is -0.23 for volatility in DH sales growth and statistically significant at the 1 percent level. The same correlation is 0.28 for regular sales growth and statistically significant at the 1 percent level. That correlation is -0.11 and insignificant for earnings growth. As the bottom right panel shows, the results are similar for firm-specific volatility in manufacturing.

Firm-specific volatility in DH sales growth appears to be counter-cyclical, while volatility in regular sales growth appears to be counter-cyclical. This difference between regular and DH growth rates may arise because we omitted the tails of the sector-level distributions of growth rates for computing regular growth rates, while observations associated with particularly large changes in the level of sales are included in the computation of DH growth rates. In that case, our findings indicate that particularly large changes in sales volumes in either direction are even more pronounced when GDP growth is weak, while other changes are more muted.

Alternatively, this different result may be due to differences in the two growth rates themselves. Relative to regular growth rates, the DH formula mutes positive growth rates but amplifies negative growth rates.[30] Possibly, this feature reduces dispersion in a boom when a relatively large number of firms has positive growth rates while it tends to increase dispersion when many firms have negative growth rates. If that is the case, the DH growth rate tends to engender counter-cyclicality by construction.

At any rate, evidence for a significant association between firm-specific volatility and the business cycle is weak as it only applies to four-quarter growth rates, while correlations with quarterly growth rates suggest that firm-specific volatility is a-cyclical.

6.2 Cyclical Properties of Dispersion

Our overall interpretation of the results in Table 3 is that there is only moderate evidence for counter-cyclicality of firm-specific volatility. This result is different from the available evidence for dispersion in firm growth rates, which so far has consistently documented counter-cyclical dispersion.[31] As we argued in Section 3, our measure better captures firm-specific volatility than dispersion measures do. However, there are other features of our approach, which we will discuss in a minute, that may explain the different results. Therefore, we now replicate the finding of Bloom, Floetotto, Jaimovich, Saporta-Eksten and Terry (2012) that the interquartile range is counter-cyclical, and then introduce the features of our estimation step by step.

[30] We show this mathematically in a footnote in Section 2.
[31] See, for instance, Bloom e.a. (2012).

Table 4 shows our results for the cyclical properties of the interquartile range. As in Bloom e.a. (2012), we computed the interquartile range (IQR) in the cross-sectional distribution of growth rates for the economy as a whole. The top third of the table pertains to the IQR in regular sales growth rates, the middle third to Davis-Haltiwanger sales growth rates, and the bottom third to earnings growth rates.

Rows labeled "dca" indicate results when we detrended the IQR by computing the percentage difference from a Hodrick-Prescott trend with smoothing parameter 16,000, cleaned the Compustat data as explained in Section 2, and include all firms irrespective of the number of available observations. Codes without "a" mean that we restrict the sample to firms with at least 100 quarters of observations available in Compustat for 1961Q1-2012Q4. Codes without "c" mean that we do not do cleaning other than selecting US firms and eliminating double observations. Codes without "d" mean that we do not de-trend the IQR.

The sample period is 1962Q2-2012Q4 for non-cleaned samples and 1978Q1-2012Q4 for cleaned samples.

Rows marked "/" aim to replicate the results from Bloom e.a. (2012). In this case, we did not do the cleaning described in Section 2, did not detrend the IQR, and restricted the sample to firms for which at least 100 quarters of observations are available in 1961Q1-2012Q4.

Excluding short-lived firms is the approach which Bloom e.a. (2012) follow to reduce the effect of changes in sample composition on quarter-on-quarter changes in dispersion. This is a reasonable step to take for a measure that does not in itself control for changes in sample composition. However, it has the disadvantage that it focuses specifically on longer-lived firms, which are not necessarily representative for the economy.

In this case, we took the data straight from Compustat except for us selecting US firms and eliminating double observations by keeping only observations for the single-longest fiscal year definition for any firm. Among others, the sample starts in 1962Q1, which we find undesirable because the number of included firms in the 1960s and 1970s is comparatively small as Compustat coverage was still expanding considerably. This tends to bias the results towards finding low but increasing dispersion in the 1960s and 1970s. Also, these samples do not exclude tail observations, which means that the cross-sectional standard deviation of growth rates other than the Davis-Haltiwanger growth rates often spike because of a few observations and are therefore uninterpretable. Bloom e.a. (2012) motivate their using the interquartile range by the fact that this measure is less affected by outliers. However, outliers still affect the distribution and therefore affect the interquartile range to some extent. We find it preferable to omit tail growth rates which could have a disproportionate effect on the results, or else to use Davis-Haltiwanger growth rates where no single observation can have an overwhelming effect on measured dispersion.

Since we did not de-trend the interquartile range in this case, we insert a linear trend in the regressions on recession indicators, just as Bloom e.a. do (2012). The linear trend has the disadvantage that, because of the low levels of volatility in the 1960s and 1970s, it tends to imply a high trend level of dispersion in the 1990s and 2000s, and therefore tends to underestimate de-trended volatility. As in Bloom e.a. (2012), we computed the correlations without de-trending. In that case, low trend levels of dispersion in the 1960s and 1970s could bias the results towards finding counter-cyclicality to the extent that trend growth in GDP is higher at that time. Note that considering only long-lived firms will help in terms of measuring quarter-on-quarter changes in dispersion, but cannot be expected to address issues with measurement of trends in volatility.

In the above case, we find that for all three growth rates, the interquartile range is significantly higher during recessions and negatively correlated with quarterly and four-quarter GDP growth.

The correlation of the IQR with annualized quarterly GDP growth is -0.27 for regular sales growth, -0.30 for DH sales growth and -0.25 for earnings growth. All these results are significant at the one percent level.

These results replicate Bloom e.a. (2012), who find that the IQR of sales growth for firms in Compustat quarterly is negatively correlated with GDP growth with a correlation of -0.275. This correlation is significant at the one percent level, as is the coefficient on the NBER recession indicator in their regression of the IQR on a constant, recession indicator and linear trend.

As the rows labeled "d" reveal, de-trending by computing the percentage difference of the interquartile range with a HP trend with smoothing parameter 16,000 leaves the result standing: the interquartile range is significantly higher during recessions, and significantly negatively correlated with GDP growth. All these results continue to be significant at the 1 percent level.

As the rows labeled "dc" reveal, cleaning the data in addition to detrending still suggests that the interquartile range is counter-cyclical, although the degree of counter-cyclicality is somewhat less prnounced. The correlations are smaller in absolute value, but still negative in all cases and mostly significant at the 5 percent level or better. The correlation with quarterly GDP growth is only -0.09 for regular sales growth, but it is -0.19 for DH sales growth and -0.17 for earnings growth. Dispersion is still higher during recessions, and this difference is significant at the five percent level or better.

This line yields an interesting result: even in a sample that starts in 1978Q1 and when using a non-linear trend, the interquartile range is counter-cyclical in a sample of firms that have at least 100 quarters available.

The row labeled "dca" shows results when we consider all firms in our cleaned sample irrespective of the number of available observations, and de-trend the IQR. In this case, earnings and regular sales growth are somewhat higher during recessions than otherwise, but the difference ceases to be statistically significant. The IQR in DH sales growth is appreciably higher during recessions than otherwise, and this difference is statistically significant at the five percent level. Correlations are mostly insignificant except for the correlation between the IQR in the DH sales growth rate and four-quarter GDP growth.

This suggests that the interquartile range is a-cyclical, or at best moderately counter-cyclical, for our full sample.

Therefore, we find that the interquartile range is robustly counter-cyclical only for a particular sample that exclusively contains long-lived firms. These results are not necessarily representative for the overall economy. On the other hand, the results for all firms irrespective of the number of available observations are likely more affected by cyclical changes in sample composition. For instance, the fraction of intrinsically volatile firms may increase during booms as a relatively large number of firms enters the stock market, while the fraction of volatile firms may decrease during recessions as volatile firms may be more likely than others to delist in slowdowns.

Furthermore, there is a large increase in the IQR during the 1981-1982 recession which is likely in part due to the aforementioned increase in Compustat coverage during that time. This would tend to imply overestimation of the degree of counter-cyclicality. Recall from Figure 2 that our measure of firm-specific volatility which controls for changes in sample composition increases during that recession. However, this increase is much less pronounced than when we do not control for changes in sample composition in the volatility regression in our full sample of firms (unreported). This is why we believe that the increase in Compustat coverage during the 1981-1982 recession tends to bias the results towards finding a counter-cyclical IQR.

Table 5 shows evidence for the cross-sectional standard deviation. Bloom e.a. (2012) do not report this case, plausibly because they do not consider cleaned samples and do not consider DH growth rates.

There is no particular evidence that the cross-sectional standard deviations be counter-cyclical. The only evidence in facor is that for non-cleaned data for long-lived firms, the cross-sectional standard deviation in DH sales growth is significantly negatively correlated with GDP growth. This applies whether we de-trend the cross-sectional standard deviation or not, as shown in the rows marked "d" and "/", respectively.

Note that this could be due to outliers in levels changes that cause spikes in the cross-sectional standard deviations for regular growth rates and still have some effect on the Davis-Haltiwanger growth rates.

When we clean the data, the results are mixed, whether we de-trend and consider all firms ("dca"), de-trend and consider long-lived firms only ("dc") or whether we do not de-trend and consider long-lived firms only ("c"). The recession incators are insignificant in all cases. Correlations for dispersion in regular sales growth tend to be positive, tend to be small for Davis-Haltiwanger sales growth, and positive but small for earnings growth.

These results suggest that the cross-sectional standard deviation is a-cyclical. While Table 3 showed that there was some evidence that might support counter-cyclicality in firm-specific volatility, the rows "dca" in Table 5 show that for cross-sectional standard deviations estimated on the same sample, there is no particular evidence for counter-cyclicality.

There is no reason why the IQR would be a better measure of dispersion than the cross-sectional standard deviation, once tail observations are omitted. Therefore, the fact that the cross-sectional standard deviation is not counter-cyclical is equally important as the finding that there is quite some evidence for counter-cyclicality in the IQR. At any rate, our measure of firm volatility is constructed to better capture the volatility of firm-specific shocks that feature in theoretical models such as the irreversibility and financial accelerator models mentioned in the introduction. From the perspective of informing theories, our finding that firm-specific volatility is only moderately counter-cyclical is therefore particularly instructive.

7 Does Firm Volatility Explain Credit Spreads and the Real Economy?

The previous section examined the contemporaneous association of firm-specific volatility with the business cycle. We found only moderate evidence for a negative association. In this section, we examine the dynamic interaction between firm volatility and the macro-economy.

In particular, we test whether shocks in firm volatility from the perspective of a recursive Vector Autoregression (VAR) contribute to explaining in-sample fluctuations in the real economy beyond the effect of lagged real growth rates. Table 6 shows the results from Granger-causality tests in a VAR including de-trended firm-specific volatility and a real activity variable. In the top half of the table, the real activity variable is annualized quarterly real GDP growth while in the bottom half it is real investment growth.[32] The left half of the table pertains to economy-wide firm-specific volatility while the right half pertains to firm-specific volatility in manufacturing. Rows labeled "Sales" pertain to firm volatility in regular sales growth, rows labeled "DH sales" to volatility in Davis-Haltiwanger sales growth, and rows labeled "Earnings" to volatility in earnings growth.

We report results from a VAR with lag order four. Columns labeled "vol = > act" test whether firm volatility Granger-causes growth in real activity. In particular, it reports the F-statistic and

[32] Investment is private nonresidential fixed investment deflated by the GDP deflator. We use real GDP, GDP deflator, and investment after the 2013 Comprehensive Review of the National Income and Product Accounts, with base year 2009.

associated p-value for joint significance of the coefficients on the lagged firm volatility terms in the VAR equation for real GDP growth. Similarly, columns labeled "act => vol" test whether growth in real activity Granger-causes firm volatility.

Firm volatility does not Granger-cause growth in real activity in any of the twelve cases reported in Table 6. That is, firm volatility does not add to explaining in-sample variation in real GDP growth or real investment growth beyond the information contained in lagged growth rates. These results are at odds with the implication from irreversibility and financial accelerator models that fluctuations in firm-specific volatility have a substantial effect on the real economy.

In three cases, growth in real activity Granger-causes firm volatility. In principle, this could reflect a slowing of the economy in anticipation of an increase in risk, as in Christiano, Motto, and Rostagno (2013). Yet in only one of these cases, the sign is as predicted by that theory: economy-wide firm-specific volatility in DH sales growth decreases after an increase in investment growth. Here as in other results below, we order real activity before firm volatility. Therefore, we assume that firm-specific volatility does not contemporaneously affect real GDP growth. We do so in order to assess the effect of shocks to firm volatility that are orthogonal to real activity.

Summing up the evidence from bivariate VARs, we find no evidence at all for the influence of unanticipated shocks to firm-specific volatility on the real economy beyond the influence of lagged growth rates. There may be some effect of future, anticipated shocks in real volatility on the real economy, but there is no particular evidence that this effect is of the sign predicted by financial accelerator theories.

Tables 7 and 8 report results from Granger causality tests in a tri-variate VAR that also includes the credit spread, measured as the spread between Moody's Baa and Aaa seasoned corporate bond yield, and de-trended as the percentage point difference from a Hodrick-Prescott trend with smoothing parameter 16,000. By including credit spreads, we are able to quantify to which extent increases in firm-specific volatility anticipate increases in credit spreads and a deterioration in the business cycle, a mechanism highlighted by Christiano, Motto, and Rostagno (2013). Another reason for including credit spreads is that Christiano e.a. (2013) find that including financial variables helps their model to distinguish the effect of firm-specific risk shocks from that of other candidate drivers of macroeconomic fluctuations.

In neither of the reported twelve cases does firm-specific volatility Granger-cause growth in real GDP or real investment. Real invesment growth does Granger-cause firm-specific volatility in Davis-Haltiwanger sales growth, this time for volatility in manufacturing as well as economy-wide firm volatility. Again, this impulse-response has the correct sign according to the impact of risk signals on the real economy. But again, the combination of Granger-causality and the correct sign only holds in a specific case.

On the other hand, the credit spread Granger-causes real activity in all twelve cases. Impulse-responses consistently show a substantial drop in investment growth after a rise in the credit spread, and a temporary decline in GDP growth after a rise in the credit spread. In all our tri-variate VARS, we order real activity growth first, firm-specific volatility second, and the credit spread last. Therefore, we assume that the credit spread does not contemporaneously affect firm-specific sales volatility or real GDP growth. We do so because the credit spread is a financial variable which should react instantaneously to news about real variables.

In one case does firm-specific volatility Granger-cause the credit spread: economy-wide firm-specific volatility in earnings growth Granger-causes the credit spread in a VAR with GDP growth at the five percent level. Significance is at the 10 percent level in the corresponding VAR with investment growth.

The corresponding impulse-responses with earnings growth volatility reveal that increases in firm volatility imply increases in the credit spread. However, this effect is strongest for economy-wide volatility, and much less strong for firm volatility in manufacturing. From the point of view of financial accelerator theories, one would expect the effect to be strongest in manufacturing which is capital-intensive. Still, it is possible that firm-specific volatility in manufacturing does relate to production in manufacturing while this effect is watered down in a test with aggregate real GDP and investment.

Figure 7 shows impulse-responses for one of the twelve specifications, the one that is most favorable to the implications of the theory of Christiano e.a. (2013) for the relation between firm volatility and the business cycle. A one-standard deviation shock to firm-specific volatility, implying a persistent rise in firm-specific volatility of 3.3 percent above trend on impact, leads to a decline in annualized real GDP growth of 0.3 percentage points. This decline is statistically insignificant at the five percent level. The rise in firm volatility implies a rise in the credit spread peaking at 0.08 percentage points above trend, which is economically small yet statistically significant.

As the leftmost column of Table 8 documents, the corresponding variance decomposition implies that at a long horizon (100 quarters), firm-specific volatility explains 15.71 percent of the forecast error variance of the credit spread, and 5.35 percent of that of real GDP growth. These shares are non-trivial, but much smaller than the variance shares in Christiano e.a. (2013). In addition, our empirical model has only three shocks while their theoretical model has twelve. As the third column of Table 8 reveals, the contribution is smaller when we consider firm-specific volatility in manufacturing: 4.18 percent and 3.90 percent, respectively.

In a VAR with investment growth, economy-wide firm-specific volatility explains 8.21 percent of the variance of the credit spread and 7.88 percent of the variance of investment growth. Firm-specific volatility in manufacturing explains 0.91 percent of variation in the credit spread and 3.39 percent of variation in investment growth.

Therefore, there is some evidence that the essential dynamics of the models of Christiano e.a. (2013) and Bloom (2009) are present in the data. In the language of the Christiano e.a. (2013) model, we find that an increase in firm risk leads to a widening in credit spreads and a slowdown in the real economy. In line with the implications of the Bloom (2009) model, we find that GDP growth initially slows down after a rise in firm-specific uncertainty, but then increases above its pre-shock level. The theory predicts such overshoot in real activity as firms carry out the investment projects and hiring activity which they postponed while uncertainty was at its peak.

However, the magnitude of the responses is small, and firm-specific volatility explains only a moderate fraction of fluctuations in the credit spread and a very small fraction of fluctuations in real GDP growth. This is evidence against the theoretical prediction that firm-specific volatility be a major driver for macroeconomic fluctuations.

8 Conclusion

In this paper, we estimated quarter-on-quarter changes in firm-specific volatility of sales and earnings growth. We find that firm-specific volatility tends to peak during, shortly before or shortly after recessions, yet there is no statistically significant negative contemporaneous association between firm-specific volatility and real output growth. Moreover, we find that changes in firm-specific volatility do not contribute significantly to in-sample fluctuations in aggregate real growth beyond the information contained in lagged growth rates. Rising firm-specific earnings growth volatility does tend to cause increasing credit spreads and tends to dampen growth in aggregate real output and investment, but these effects are quantitatively small and account for a small share of fluctuations in macroeconomic variables.

Therefore, our evidence suggests that turnover in market shares and in profit shares may be higher during or around the time of recessions, but that this increased turbulence is not a main driver of macro fluctuations. There is no strong and robust dynamic relation in either direction between firm volatility and the business cycle. In crisis periods, firms may be adapting to a new environment and this may lead to higher turnover as well as a slowdown in aggregate growth, without these two effects needing to coincide in terms of timing.

Furthermore, we find that the trend increase in the volatility of publicly traded firms is completely overturned when we control for changes in sample composition. An individual publicly traded firm was less volatile at the end of our sample period, in 2012, than it was at the beginning, in 1978. At the firm level, a temporary increase in volatility during the 2007-09 recession did not end the Great Moderation.

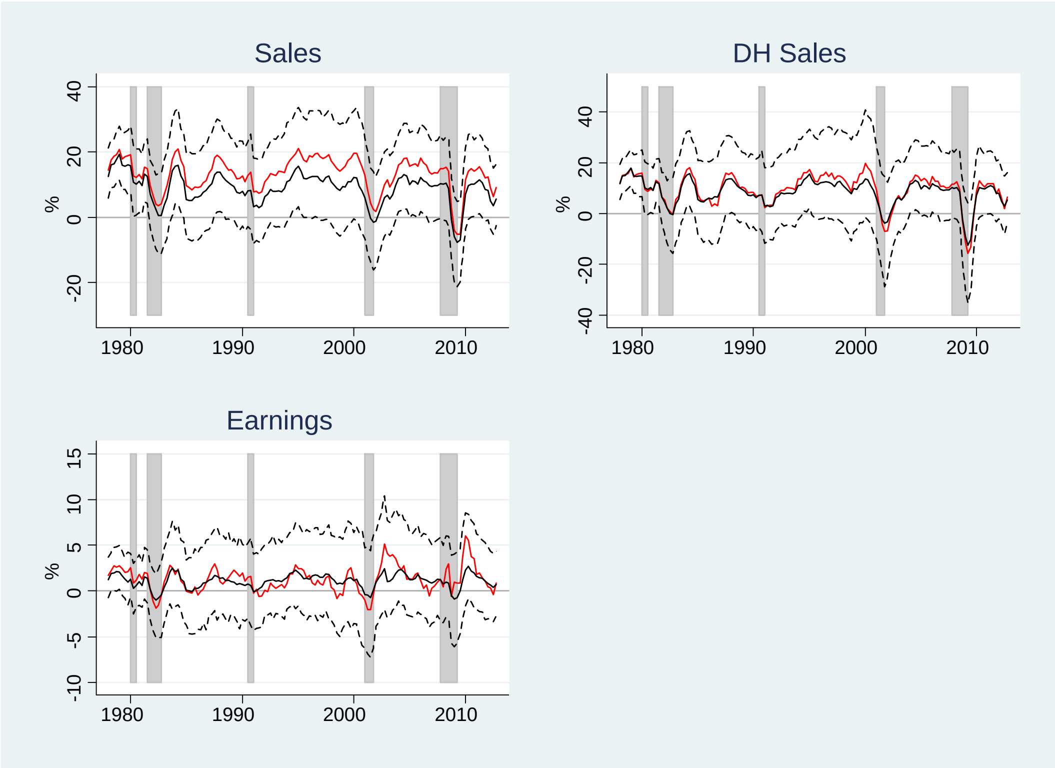
We also find consistent medium-run patterns in firm volatility. Recession coincide with turning points in firm volatility. Volatility increases during the recessions of the early 1980s. It then decreases until the 1990-91 recession. It then increases until the 2001 recession. It then decreases until the 2007-09 recession. At this stage, we do not have an explanation for these medium-run patterns in firm volatility. Possibly, firms' attitude to risk changes as a result of the extent to which risk materializes. The recessions of the early 1980s and the 1987 stock market crash may have contributed to firms taking less risk, resulting in a decrease in realized firm volatility. During the productivity acceleration of the second half of the 1990s, firms may have placed lower subjective probabilities on adverse outcomes, and therefore may have taken more risk, with firm volatility increasing as a result. Firm volatility declined sharply after the 2001 recession, so there may have been something special about this recession which raised firms' subjective probabilities of a negative event.

Our measure improves on dispersion measures in terms of capturing firm-specific shocks and uncertainty. Further improvements could involve controlling for a broader set of factors, such as lagged growth rates, which could account for predictable changes in firm-level growth.

To make further progress in modeling any relation between firm-specific volatility and the macro-economy, it is essential to use the best available estimate for firm-specific volatility. Since our measure is computed from firm level data, it would be interesting to enter our series of firm-specific volatility as an observable variable to estimated irreversibility or financial accelerator models.

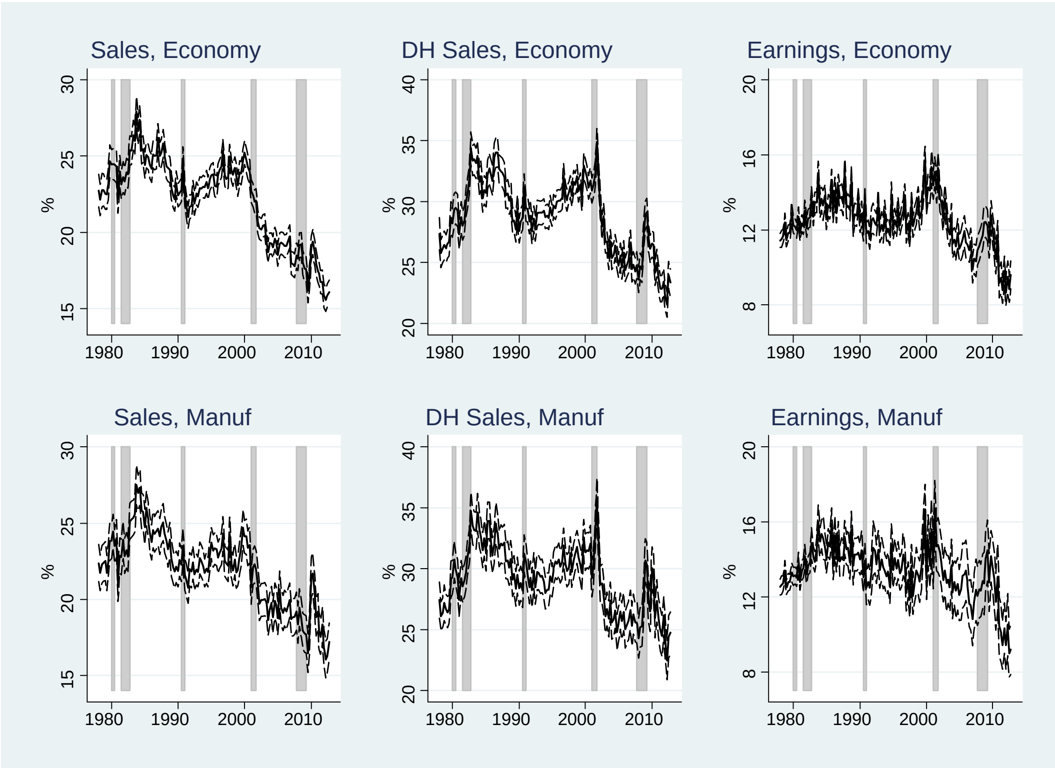
Figures and Tables

Figure 1
Mean and Quartiles of Sales and Earnings Growth



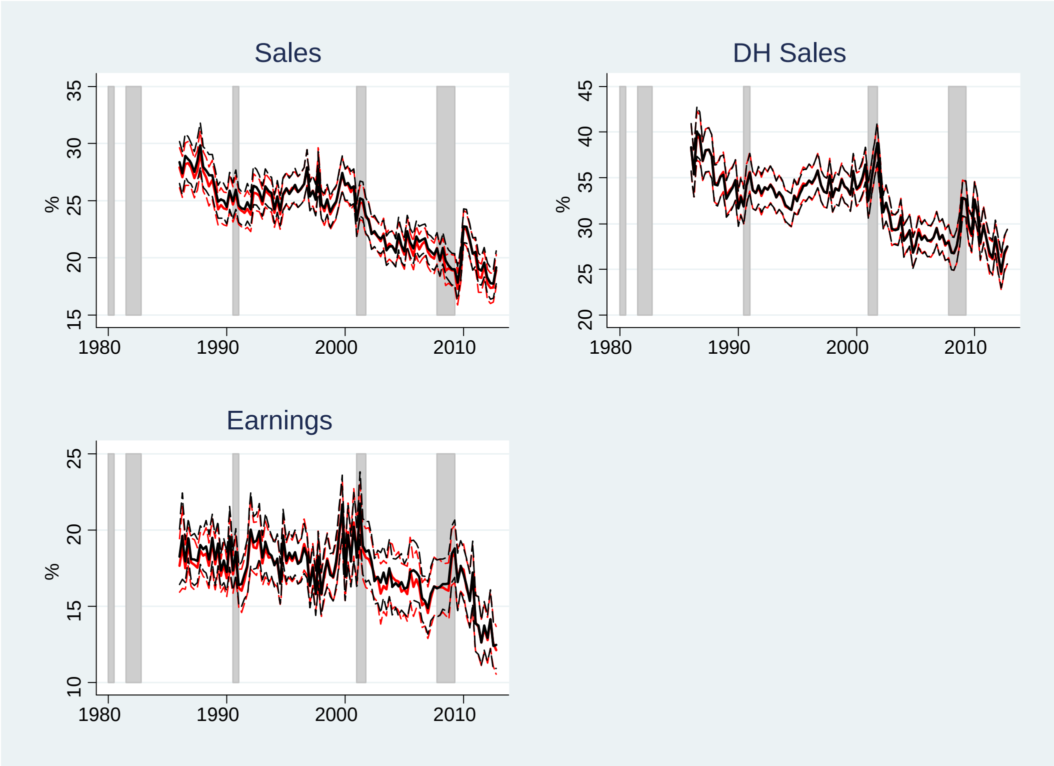
Note: This figure documents the cross-sectional distribution of growth rates for every quarter in our Compustat sample of US firms for 1978Q1-2012Q4, cleaned as explained in Section 2. Solid black lines are medians, dashed lines 25th and 75th percentiles, while the solid red line is the mean growth rate. Growth rates indicate the percentage change in sales or earnings with respect to four quarters before. The figure labeled "Sales" pertains to the regular sales growth rate (1), the figure "DH sales" to the Davis-Haltiwanger sales growth rate (2), and the figure "Earnings" to earnings growth (3). Shaded areas are NBER recessions.

Figure 2
Firm-Specific Sales and Earnings Volatility: Economy and Manufacturing Sector



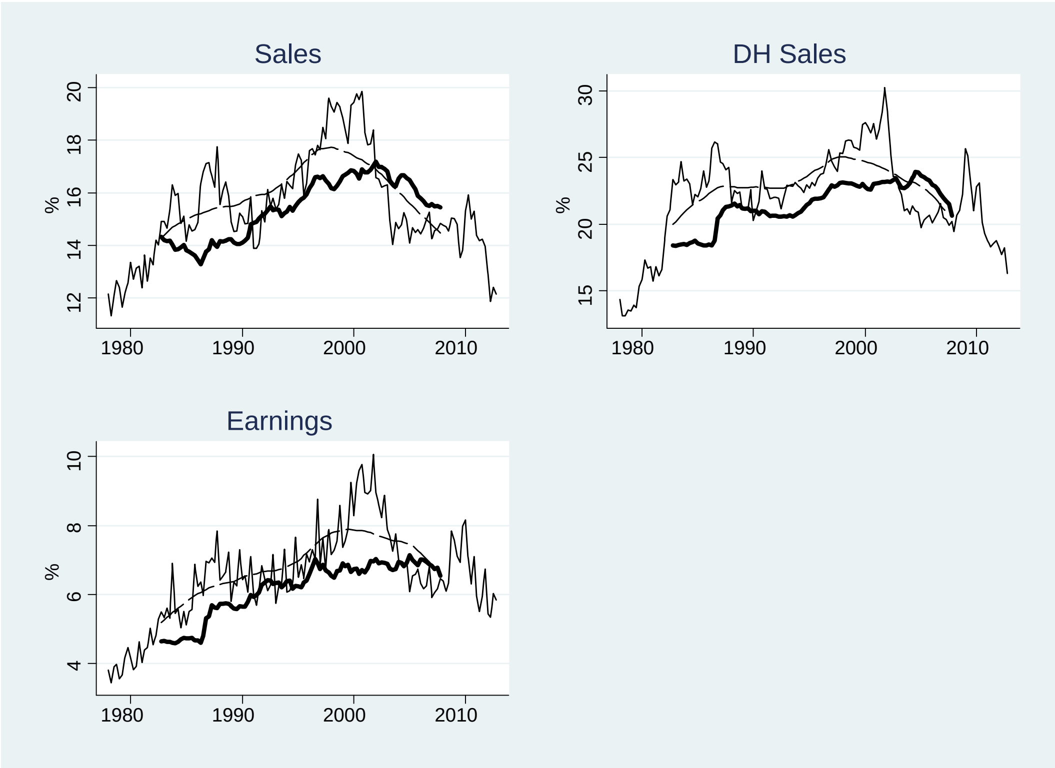
Note: This figure shows firm-specific volatility for nominal growth rates estimated using equations (4) through (6), along with 95 percent confidence intervals. The top row pertains to results for the overall economy, while the bottom row pertains to the manufacturing sector. From left to right, volatility is in regular sales growth (1), Davis-Haltiwanger sales growth (2), and earnings growth (3). In this graph, firm volatility is not seasonally adjusted and not detrended. Units are percentages, in the sense that the level of firm volatility in any quarter indicates the size of a one-standard deviation percentage change in sales or earnings with respect to four quarters before. The sample is 1978Q1-2012Q4. Shaded areas indicate NBER recessions.

Figure 3
Firm-specific Volatility in Nominal vs. Real Growth Rates



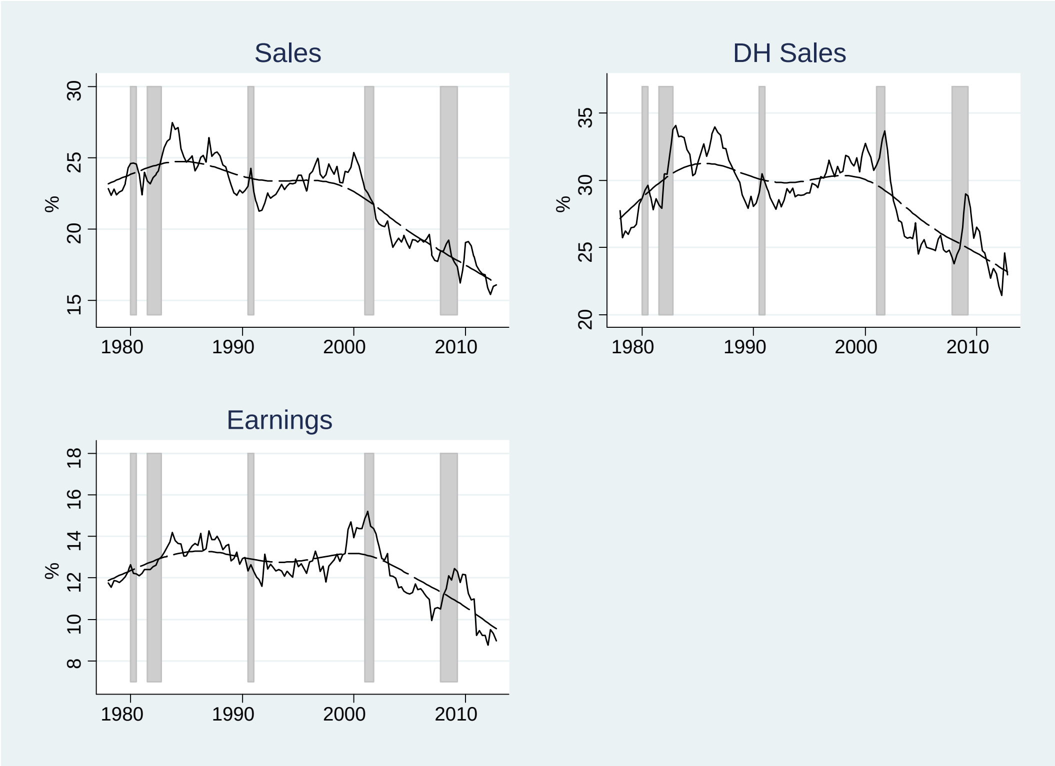
Note: This figure shows firm-specific volatility for part of the manufacturing sector estimated using equations (4) through (6), along with 95 percent confidence intervals. Black lines are firm volatility in the growth rates of nominal sales and earnings, while red lines correspond to firm volatility in the growth rates of real sales and earnings. We computed real sales and earnings by deflating nominal sales and earnings by the Producer Price Index (PPI) at the 6-digit NAICS level. Both nominal and real results in this graph are for those observations in our cleaned Compustat sample for which the 6-digit PPI is available from the Bureau of Labor Statistics. Among those observations, we dropped sectors for which there was an insufficient number of firms left in many quarters: all non-manufacturing sectors as well as the manufacturing sectors 313 Textile mills, 314 Textile product mills and 315 Apparal manufacturing, as well as the sectors 322 Paper manufacturing and 326 Plastics and rubber products manufacturing. For similar reasons, we restrict the sample to 1986Q1-2012Q4. In this graph, firm volatility is not seasonally adjusted and not detrended. Shaded areas indicate NBER recessions. Units are as in Figure 2. “Sales” indicates firm-specific volatility in regular sales growth (1); “DH sales” in Davis-Haltiwanger sales growth (2); “Earnings” in earnings growth (3).

Figure 4
Rolling Standard Deviations vs. Firm-Specific Volatility



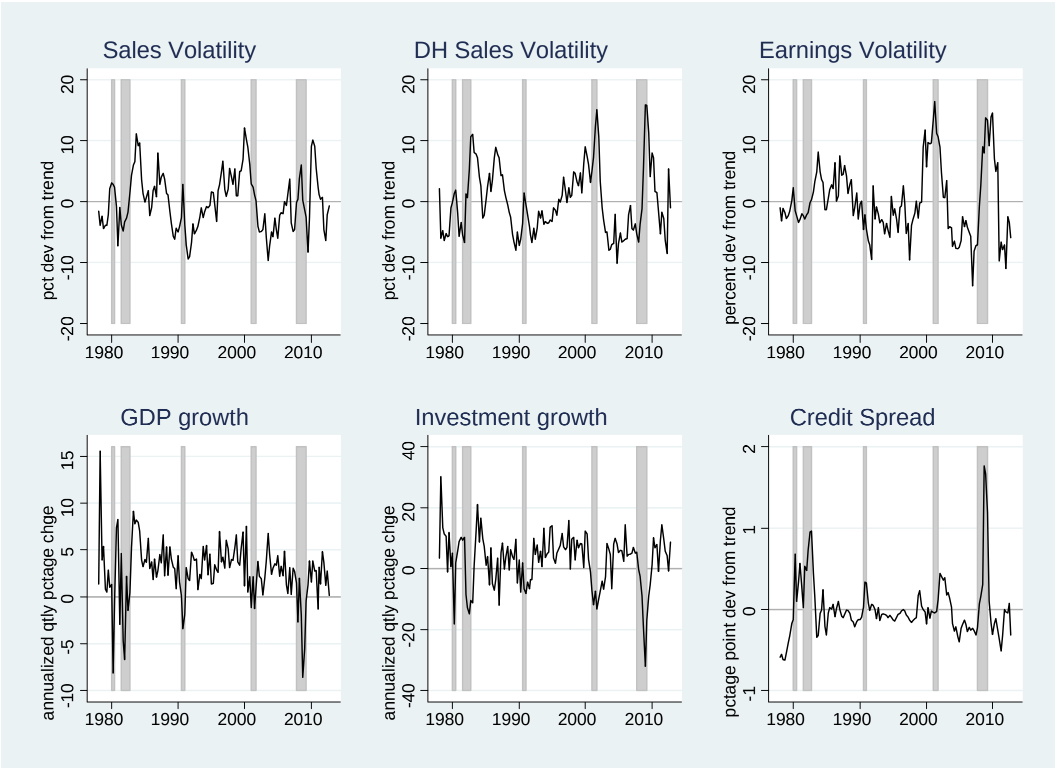
Note: The bold lines plot the cross-sectional average of centered forty-quarter rolling standard deviations for nominal sales and earnings growth in our cleaned Compustat sample. The thin solid lines are estimates of firm-specific volatility on the same sample using equations (4), (5) as well as a variant of the volatility regression, equation (6), that does not include firm fixed effects. Therefore, neither measure controls for changes in sample composition. Both the rolling standard deviations and firm-specific volatility in this graph are for observations that are part of a spell of at least forty consecutive quarters of available observations for a firm. The long dashed lines are centered forty-quarter averages of the estimates of firm-specific volatility shown on these graphs. Units are as in Figure 2. “Sales” indicates volatility in regular sales growth (1); “DH sales” in Davis-Haltiwanger sales growth (2); “Earnings” in earnings growth (3).

Figure 5
Firm-Specific Volatility and Trend



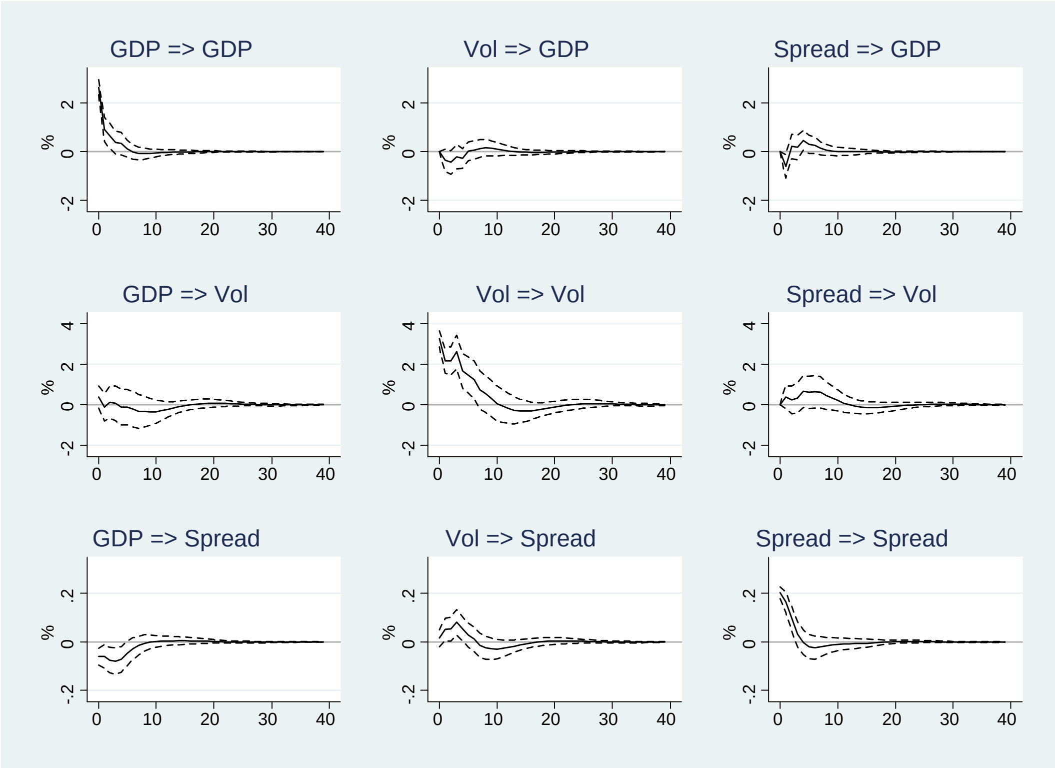
Note: In this figure, the solid line is firm-specific volatility in nominal sales and earnings growth for the overall economy, estimated using equations (4) through (6), and after multiplicative X12 seasonal adjustment. The long dashed lines are Hodrick-Prescott filter trends of seasonally adjusted firm-specific volatility. Units are as in Figure 2. “Sales” indicates volatility in regular sales growth (1); “DH sales” in Davis-Haltiwanger sales growth (2); “Earnings” in earnings growth (3).

Figure 6
De-Trended Firm-Specific Volatility, Growth in Real Activity, De-Trended Credit Spread



Note: This graph plots data we use in our time series analysis in Sections 5 through 7. The top row plots, from left to right, de-trended firm-specific volatility in regular sales growth (1), Davis-Haltiwanger sales growth (2), and earnings growth (3), estimated using equations (4) through (6). We obtain these series from the series in the top row of Figure 2 by first seasonally adjusting firm-specific volatility using the multiplicative X12 procedure, and then de-trending the seasonally adjusted series by computing the percentage difference from a Hodrick-Prescott trend with smoothing parameter lamdba=16,000. The bottom row shows, from left to right, the annualized quarterly percentage change in real GDP, the annualized quarterly percentage change in real investment, and the de-trended credit spread. The credit spread is the spread between Moody's Baa and Aaa seasoned corporate bond yields in percent per year, stated as the arithmetic difference from its Hodrick-Prescott trend with smoothing parameter 16,000.

Figure 7
Firm-Specific Earnings Volatility, Credit Spread, Real GDP Growth: Impulse Responses



Note: This figure shows impulse-responses for a Vector Autoregression (VAR) with annualized quarterly real GDP growth, de-trended economy-wide firm-specific earnings volatility and the de-trended credit spread, along with 95 percent confidence bands. These are among the variables plotted in Figure 6. In the titles for individual panels, "GDP" stands for real GDP growth, "Vol" for firm-specific earnings volatility, and "Spread" for the credit spread. The figure title "Vol => GDP" means that the figure shows the response of GDP growth to an impulse in firm-specific earnings volatility. Analogous meanings apply to the titles of the other panels. These results are for a VAR with lag order four, and for a Cholesky decomposition that orders GDP growth first, firm-specific volatility second, and the credit spread third.

Table 1
Observations and Sales-to-GDP Ratios by Two-Digit NAICS Sector

2-digit NAICS sector	Total obs	Avg obs	Med sal-GDP
21 Mining, quarrying, and oil and gas extraction	20,925	149	0.0011%
23 Construction	6,837	49	0.0031%
31-33 Manufacturing	173,968	–	0.0017%
42 Wholesale Trade	16,138	115	0.0036%
44-45 Retail Trade	11,636	83	0.0051%
48-49 Transportation and Warehousing	12,481	89	0.0054%
51 Information	43,470	311	0.0011%
53 Real estate and rental and leasing	18,505	132	0.0009%
54 Professional, scientific, and technical services	20,918	149	0.0008%
56 Administrative and support and			
waste management and remediation services	10,368	74	0.0018%
62 Health care and social assistance	9,252	66	0.0015%
72 Accommodation and food services	9,433	67	0.0018%
Total	353,931	–	0.0017%

Note: This table lists the two-digit NAICS sectors, the number of observations by sector and the median sales-to-GDP ratio in our cleaned sample for 1978q1-2012. We excluded NAICS sectors 22 Utilities and 52 Finance and insurance, as well as firms without a NAICS code and non-classified firms. We only included sectors that have at least 15 observations in all but a small number of quarters. For this reason, we excluded NAICS sectors 11 Agriculture, forestry, fishing and hunting; 61 Educational services; 71 Arts, entertainment, and recreation; 81 Other services. All statistics are after omitting the top and bottom deciles of the growth distributions by sector, so that the table applies to the samples for regular sales growth (1) and earnings growth (3). The samples for Davis-Haltiwanger sales growth (2) are larger. The first column shows the total number of firms by sector. The second column shows the average quarterly number of observations for every sector for which we run the growth rate regression (4). The rightmost column shows the median sales-to-GDP ratio by sector, where any firm's sales-to-GDP ratio in quarter t is sales in the year ending in that quarter as a percentage of GDP for the same period.

Table 2
Observations and Sales-to-GDP Ratios by Three-Digit NAICS Sector in Manufacturing

3-digit NAICS sector	Total obs	Avg obs	Med sal-GDP
311 Food manufacturing and 312 Beverage and tobacco product manufacturing	8,563	61	0.0064%
313 Textile mills, 314 Textile product mills and 315 Apparel manufacturing	5,787	41	0.0037%
322 Paper manufacturing	4,150	30	0.0121%
324 Petroleum and coal products manufacturing	2,756	20	0.0396%
325 Chemical manufacturing	31,922	228	0.0010%
326 Plastics and rubber products manufacturing	5,207	37	0.0022%
331 Primary steel manufacturing	5,694	41	0.0075%
332 Fabricated metal product manufacturing	7,938	57	0.0028%
333 Machinery manufacturing	17,817	127	0.0018%
334 Computer and electronic product manufacturing	53,825	384	0.0009%
335 Electrical equipment, appliance, and component manufacturing	7,490	54	0.0023%
336 Transportation equipment manufacturing	9,909	71	0.0061%
339 Miscellaneous manufacturing	12,910	92	0.0008%
Total manufacturing	173,968	–	0.0017%

Note: This table shows the 3-digit NAICS sectors within manufacturing, the number of observations by sector and the median sales-to-GDP ratio in our cleaned sample for 1978q1-2012. We excluded manufacturing firms for which no 3-digit NAICS code was available. We use sectors that have at least 15 observations in all but a small number of quarters. To this end, we combined sectors 311 and 312, as well as sectors 313, 314 and 315. We excluded sectors 316 Leather and allied product manufacturing; 321 Wood product manufacturing; 323 Printing and related support activities; 327 Nonmetallic mineral product manufacturing; 337 furniture and related product manufacturing. Other notes are as under Table 1.

Table 3
Firm-Specific Volatility: Cyclical Properties

		Regression on Recession Dates			Correlation.	
		constant	rec	R^2 / $\overline{R^2}$	gdpg1	gdpg4
Agg.	Sales	$-$**0.08** (0.84)	**0.23** (1.14)	0.00 / – 0.01	**0.11**	**0.28****
	DH	$-$**0.65** (0.88)	**3.53** (1.99)	0.06 / 0.05	$-$**0.09**	$-$**0.23****
	Earn.	$-$**0.67** (0.90)	**3.67** (2.30)	0.05 / 0.05	$-$**0.04**	$-$**0.11**
Manuf.	Sales	**0.15** (0.87)	$-$**1.13** (1.23)	0.01 / 0.00	**0.16**	**0.33****
	DH	$-$**0.58** (0.84)	**3.20** (2.01)	0.05 / 0.04	$-$**0.05**	$-$**0.18***
	Earn.	$-$**0.55** (0.93)	**3.04** (2.26)	0.03 / 0.02	**0.01**	$-$**0.07**

Note: The left part of the table reports results from regressing de-trended firm-specific volatility on a constant and "rec", a recession indicator which is one when the economy is in recession according to the NBER business cycle reference dates and zero otherwise. Bold figures are point estimates and figures in brackets are Newey-West standard errors. The right part of the table reports Pearson correlations of firm-specific volatility with GDP growth. In the column labeled "gdpg1", the latter is the annualized quarterly percentage change in real GDP, while in the column labeled "gdpg4" it is the percentage change in real GDP with respect to four quarters before. The top half of the table pertains to firm-specific volatility for the overall economy and the bottom half to firm volatility for the manufacturing sector. Rows labeled "Sales" pertain to firm volatility in regular sales growth (1), rows labeled "DH" to volatility in Davis-Haltiwanger sales growth (2), and "Earn." to volatility in earnings growth (3). De-trended firm-specific volatility is as plotted in the top row of Figure 6 and is computed as explained under that table. De-trended firm-specific volatility for the manufacturing sector is computed in the same fashion as economy-wide firm-specific volatility. Annualized quarterly real GDP growth is as plotted in the bottom left panel of Figure 6. ** and * indicate significance at the 1% and 5% levels, respectively.

Table 4
Interquartile Range: Cyclical Properties

		Regression on Recession Dates				Correlation	
		constant	rec	trend	$\overline{R^2}$	gdpg1	gdpg4
Sales	/	**14.92**** (1.09)	**2.82**** (0.92)	**0.03**** (0.01)	0.28	**−0.27****	**−0.40****
	d	**−1.91** (1.74)	**10.62**** (3.58)	N/A	0.06	**−0.28****	**−0.38****
	dc	**−1.39** (1.61)	**7.43**** (2.54)	N/A	0.07	**−0.09**	**−0.18***
	dca	**−0.60** (1.38)	**2.52** (1.67)	N/A	0.01	**0.05**	**0.07**
DH	/	**12.86**** (0.94)	**3.14**** (0.83)	**0.04**** (0.01)	0.37	**−0.30****	**−0.50****
	d	**−2.52** (1.84)	**14.16**** (3.92)	N/A	0.09	**−0.29****	**−0.50****
	dc	**−2.66** (1.86)	**14.28**** (5.38)	N/A	0.13	**−0.19***	**−0.43****
	dca	**−1.69** (1.78)	**7.93*** (3.84)	N/A	0.06	**−0.08**	**−0.26****
Earn.	/	**6.21**** (0.50)	**1.25**** (0.43)	**0.001** (0.004)	0.10	**−0.25****	**−0.36****
	d	**−2.33** (1.73)	**11.06**** (3.63)	N/A	0.07	**−0.22****	**−0.32****
	dc	**−1.73** (1.66)	**9.18*** (4.10)	N/A	0.08	**−0.17***	**−0.22***
	dca	**−0.53** (1.22)	**1.66** (2.45)	N/A	0.00	**0.01**	**−0.01**

Note: The left part of the table reports results from regressing the interquartile range (IQR) for sales or earnings growth on a constant and "rec", the NBER recession indicator explained under Table 3. For non-detrended IQRs, we include a linear trend ("trend") in the regression. Bold figures are point estimates and figures in brackets are Newey-West standard errors. As in Table 3, the right part of the table reports correlations with real GDP growth. The top third of the table reports results for the IQR for regular sales growth (1), the middle for Davis-Haltiwanger sales growth (2), and the bottom third for earnings growth (3). For rows labeled "dca", we detrended the IQR by computing the percentage difference from a Hodrick-Prescott trend with smoothing parameter 16,000, cleaned the Compustat data as explained in Section 2, and included all firms irrespective of the number of available observations. For rows labeled "dc", data are the same as for "dca" except for us restricting the sample to firms with at least 100 quarters of observations available in Compustat for 1961Q1-2012Q4. For rows labeled "d", data are the same as for "dc" except for us not doing any cleaning other than selecting US firms and eliminating double observations. For rows labeled "/", data are the same as for "d" except for us not de-trending the IQR. Results are for economy-wide IQRs, seasonally adjusted using X12 multiplicative seasonal adjustment. ** and * indicate significance at the 1% and 5% levels, respectively.

Table 5
Cross-Sectional Standard Deviation: Cyclical Properties

		Regression on Recession Dates				Correlation	
		constant	rec	trend	$\overline{R^2}$	gdpg1	gdpg4
Sales	c	**21.34**** (1.57)	**−0.68** (0.57)	**−0.01** (0.01)	0.05	**0.22****	**0.36****
	dc	**0.05** (1.41)	**−1.10** (2.25)	N/A	0.00	**0.13**	**0.25****
	dca	**−0.08** (0.98)	**−0.08** (1.76)	N/A	−0.01	**0.16**	**0.29****
DH	/	**20.26**** (1.20)	**0.75** (0.88)	**0.04**** (0.01)	0.31	**−0.15***	**−0.24****
	d	**−1.00** (1.49)	**4.16** (2.59)	N/A	0.01	**−0.15***	**−0.28****
	c	**23.56**** (2.72)	**0.29** (1.05)	**−0.002** (0.017)	−0.01	**0.07**	**0.00**
	dc	**−0.90** (1.39)	**4.17** (3.57)	N/A	0.02	**−0.03**	**−0.18***
	dca	**−0.48** (1.16)	**1.48** (2.51)	N/A	0.00	**0.06**	**−0.05**
Earn.	c	**8.19**** (1.08)	**−0.08** (0.53)	**0.008** (0.007)	0.01	**0.09**	**0.16**
	dc	**−0.21** (2.31)	**−0.67** (5.01)	N/A	−0.01	**0.11**	**0.19***
	dca	**−0.03** (1.31)	**−1.35** (3.30)	N/A	0.00	**0.17***	**0.21***

Notes are the same as under Table 4, reading "cross-sectional standard deviation" instead of "interquartile range" or "IQR".

Table 6
Firm-Specific Volatility and Real Activity Growth: Granger Causality Tests

Real activity: growth in...	Firm-specific volatility in...	Economy-wide volatility: vol => act	Economy-wide volatility: act => vol	Volatility in manufacturing: vol => act	Volatility in manufacturing: act => vol
GDP	Sales	**0.89** (0.47)	**3.15*** (0.02)	**1.00** (0.41)	**2.73*** (0.03)
	DH sales	**1.83** (0.13)	**1.52** (0.20)	**1.82** (0.13)	**1.41** (0.23)
	Earnings	**0.69** (0.60)	**0.50** (0.73)	**0.40** (0.81)	**0.35** (0.84)
Investment	Sales	**0.98** (0.42)	**1.49** (0.21)	**0.52** (0.72)	**2.29** (0.06)
	DH sales	**0.58** (0.68)	**3.35*** (0.01)	**0.60** (0.67)	**1.74** (0.15)
	Earnings	**0.95** (0.44)	**0.60** (0.66)	**0.35** (0.85)	**1.00** (0.41)

Note: This table reports results of Granger causality tests for bi-variate VARs with de-trended firm-specific volatility and a measure of growth in real activity. In the top half of the table, that measure is annualized quarterly real GDP growth, while in the bottom half it is annualized quarterly investment growth. The left part of the table pertains to economy-wide firm-specific volatility while the right part of the table pertains to firm-specific volatility in the manufacturing sector. De-trended economy-wide firm-specific volatility, real GDP growth and real investment growth are as plotted in Figure 6 and computed as explained under that figure. De-trended firm-specific volatility for the manufacturing sector is computed in the same fashion as economy-wide firm-specific volatility. These results are for VARs with lag order four. Bold figures are F-statistics and the figures in brackets are the associated p-values.. Columns labeled "vol => act" report test results for whether firm-specific volatility Granger-causes real activity growth. Columns labeled "act => vol" report test results for whether real activity growth Granger-causes firm-specific volatility. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

Table 7
Firm-Specific Volatility, Real Activity and Interest Spreads: Granger Causality Tests

	Growth in...	Vol in...	vol=>act	act=>vol	i=>act	act=>i	i=>vol	vol=>i
Econ.	GDP	Sales	**0.62**	**0.58**	**3.54****	**1.86**	**4.51****	**1.69**
		DH	**1.28**	**1.12**	**3.27***	**1.65**	**3.30***	**1.08**
		Earn.	**0.78**	**0.30**	**3.92****	**2.16**	**1.05**	**2.75***
	Invest.	Sales	**0.85**	**0.72**	**5.27****	**0.64**	**6.44****	**1.35**
		DH	**0.16**	**5.47****	**4.93****	**0.69**	**5.93****	**1.01**
		Earn.	**1.22**	**0.16**	**5.73****	**0.89**	**0.81**	**2.36**
Manuf.	GDP	Sales	**1.67**	**0.56**	**4.57****	**1.50**	**7.47****	**1.00**
		DH	**1.34**	**0.82**	**3.35***	**1.41**	**3.14***	**0.68**
		Earn.	**0.76**	**0.18**	**4.21****	**1.84**	**2.75***	**1.17**
	Invest.	Sales	**0.41**	**0.95**	**5.27****	**0.63**	**8.45****	**1.02**
		DH	**0.16**	**3.21***	**4.90****	**0.63**	**5.36****	**0.78**
		Earn.	**0.83**	**0.02**	**5.96****	**0.89**	**1.92**	**1.11**

Note: This table reports F-statistics of Granger causality tests for tri-variate VARs with a real activity variable, de-trended firm-specific volatility and a de-trended credit spread. The table reports results for VARs with four lags. The top half of the table pertains to economy-wide firm-specific volatility while the bottom half is for firm volatility in manufacturing. In each case, we show results for two alternative activity variables: annualized quarterly growth in real GDP and annualized quarterly growth in real investment. Rows labeled "Sales" pertain to firm-specific volatility in regular sales growth (1), rows labeled "DH" in Davis-Haltiwanger sales growth (2), and rows labeled "Earn." to earnings growth (3). Each column pertains to one direction of Granger-causation between the same two variables, with "vol" standing for firm-specific volatility, "act" for growth in real activity, and "i" for the credit spread. For instance, the column labeled "vol => act" pertains to tests on whether firm-specific volatility Granger-causes growth in real activity. De-trended economy-wide firm-specific volatility, GDP growth, investment growth, and the de-trended credit spread are as plotted in Figure 6 and are computed as explained under that figure. De-trended firm-specific volatility for the manufacturing sector is computed in the same fashion as economy-wide firm-specific volatility. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

Table 8
Variance Decomposition with Firm-Specific Earnings Volatility

		Economy-wide volatility		Volatility in manufacturing	
Share of...	Explained by...	act=GDP	act=inv	act=GDP	act=inv
act	act	**86.20**	**78.68**	**86.81**	**80.73**
	vol	**5.35**	**7.88**	**3.90**	**3.39**
	i	**8.45**	**13.45**	**9.29**	**15.89**
vol	act	**2.47**	**9.17**	**4.61**	**9.14**
	vol	**91.27**	**84.82**	**82.89**	**79.59**
	i	**6.27**	**6.02**	**12.50**	**11.27**
i	act	**21.69**	**21.13**	**25.84**	**22.31**
	vol	**15.71**	**8.21**	**4.18**	**0.91**
	i	**62.59**	**70.66**	**69.98**	**76.77**

Note: For tri-variate VARs with de-trended firm-specific earnings growth volatility, a measure of real activity growth and a de-trended credit spread, this table reports the share, in percent, of the 100-quarter ahead forecast error variance of the variable indicated in the first column explained by the variable indicated in the second row. "act" denotes real activity growth, "vol" firm-specific earnings volatility, and "i" the credit spread. Firm-specific earnings volatility is for the overall economy in the left half of the table and for manufacturing in the right half of the table. The activity variable is annualized quarterly growth in real GDP for columns labeled "act=GDP" and annualized quarterly growth in real investment for columns labeled "act=investment". De-trended economy-wide firm-specific volatility, GDP growth, investment growth, and the de-trended credit spread are as plotted in Figure 6 and are computed as explained under that figure. De-trended firm-specific volatility for the manufacturing sector is computed in the same fashion as economy-wide firm-specific volatility. These results are for a VAR with lag order four, and for a Cholesky decomposition that orders GDP growth first, firm-specific volatility second, and the credit spread third.

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