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Cyclical Changes in Firm Volatility

We characterize trends and cycles in the volatility of U.S. firms using a measure that we argue more cleanly captures firm-specific volatility in sales and earnings growth than standard measures do. While earlier literature has emphasized a trend increase in the volatility of publicly traded firms, we find that a typical publicly traded firm has become more stable. We find that the negative association between firm-specific volatility and the business cycle is weaker than earlier research based on dispersion measures suggests. We find that during the Great Recession of 2007–2009, firm-specific volatility increased moderately but never substantially exceeded its sample mean. Our results are inconsistent with the hypothesis that firm-specific volatility is an important driver of the business cycle, as it theoretically could be through an effect of default risk on credit spreads.

JEL codes: C32, C33, D22, E32
Keywords: firm-specific volatility, uncertainty, risk, idiosyncratic volatility.

THE LITERATURE CONSIDERS IT AN ESTABLISHED fact that microeconomic volatility, often interpreted as a measure of uncertainty or risk, is unambiguously countercyclical and rises sharply in recessions, including during the

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Great Recession of 2007–2009. The overview paper of Bloom (2014) epitomizes this perspective. As for evidence with firm-level economic data, the main point of empirical support for this view is in Bloom et al. (2014).

Recent theoretical work proposes several possible explanations for such a negative relation between the business cycle and the volatility of firm-specific shocks. In the financial accelerator model of Christiano, Motto, and Rostagno (2014), a widening in the distribution of idiosyncratic productivity shocks increases the fraction of loan defaults and the external finance premium, which causes a slowdown in aggregate investment and output. In the irreversibility models of Bloom (2009) and Bloom et al. (2014), a surge in microeconomic uncertainty causes firms to postpone investment and hiring, which accounts for a short-lived negative effect on aggregate output. In other theories, causality runs the other way, with changes in firm volatility modeled to be endogenous to aggregate fluctuations.[1]

In this paper, we reexamine the cyclical properties of firm-specific volatility using a measure that we argue more cleanly estimates idiosyncratic volatility than standard measures do. In particular, the empirical evidence of Bloom et al. (2014) relies on measures of cross-sectional dispersion such as the interquartile range (IQR) of firm-level sales growth.[2] Dispersion measures filter out aggregate variation and are therefore a natural proxy for volatility originating from shocks to individual firms. However, dispersion measures reflect a range of reasons for cross-firm differences in growth rates besides firm-specific shocks. For instance, firms can grow at a different pace because they have different growth trends or because they belong to different sectors, neither of which reflects firm-specific shocks.

To remedy for this, we estimate quarterly volatility of the part of firm-level sales and earnings growth that cannot be explained by aggregate, sector-level, and size-related factors nor by firm-specific trends. Because we control for a wider range of factors than dispersion measures do, we argue that our measure yields a cleaner estimate of the volatility of firm-specific shocks.[3]

Another difference is that unlike dispersion measures, our estimator controls for changes in sample composition. The advantage of this is that we do not have to restrict the sample in ways that would reduce the extent of compositional changes, such that we use a larger, and presumably more representative, sample of firms than in Bloom et al. (2014).

1. In addition to the models referenced in the main text, models with financial frictions and time-varying firm-specific volatility include Arellano, Bai, and Kehoe (2012), Gilchrist, Sim, and Zakrajsek (2014), and Chugh (2016), while irreversibility models include Bachmann and Bayer (2013). See Narita (2011) for a model where uncertainty affects aggregate output by exacerbating agency problems. Models with endogenous uncertainty, firm volatility, or dispersion include Van Nieuwerburgh and Veldkamp (2006), Bachmann and Moscarini (2012), Christiano and Ikeda (2013), Kehrig (2015), and Decker, D'Erasmo, and Moscoso Boedo (2016).

2. Higson, Holly, and Kattuman (2002) also find that dispersion in firm-level sales growth of U.S. firms is countercyclical.

3. De Veirman and Levin (2012) use a similar approach to estimate firm-specific volatility for Japanese firms. Castro, Clementi, and Lee (2015) apply a similar method to differences in volatility across sectors. See also Decker, D'Erasmo, and Moscoso Boedo (2016).

Our first finding pertains to volatility trends. While we replicate the finding from Comin and Philippon (2005) that there was a trend increase in sales growth volatility for publicly traded U.S. firms, we find that any evidence for a trend increase disappears once we control for sample composition.[4] There is some evidence for a downward trend, with a typical publicly traded firm being more stable in the 2000s than in the two preceding decades.

We find that our measure of firm-specific volatility is at most moderately countercyclical. Detrended sales growth volatility has a correlation of −0.09 with quarterly real gross domestic product (GDP) growth that is not statistically significantly different from zero. Firm-specific sales and earnings volatility increase moderately in recessions. This applies to the Great Recession: firm-specific volatility in sales growth, expressed as a standard deviation, rises by 17% from the quarter before the 2007Q4–2009Q2 recession to its peak in 2009Q1. Against the backdrop of the trend decline in volatility, we find that firm-specific volatility never substantially exceeds its sample mean during the Great Recession.

With comparable data processing, we find that the IQR is more strongly countercyclical than our measure of firm-specific volatility. The contrast is particularly sharp during the Great Recession, when the IQR for sales growth doubles, peaking at a level that is 3.76 standard deviations above its sample mean. Our interpretation is that the negative association between firm-specific volatility and the business cycle is weaker than evidence with the IQR such as that in Bloom et al. (2014) suggests.

As for the dynamic relation with the macroeconomy, we find that increases in firm-specific volatility are followed by at most a small increase in the credit spread and a small decline in real GDP growth. We also find that shocks to firm-specific volatility account for a small fraction of fluctuations in GDP and investment growth. Finally, we find that recent changes in firm-specific volatility do not significantly add to explaining in-sample variation in GDP or investment growth beyond the information contained in lagged growth rates.

These results are at odds with the hypothesis that changes in firm-specific volatility have a substantial negative effect on subsequent changes in GDP growth, for instance, through the mechanism of Christiano, Motto, and Rostagno (2014). Our assessment is that the moderate degree of countercyclicality that we find reflects a moderate degree of endogeneity in firm-specific volatility, in the sense that economic booms make firms somewhat less volatile.

In that we analyze the dynamic relation between firm-specific volatility and aggregate real activity, our empirical evidence is more direct in this respect than that in Bloom (2009). That paper shows the dynamic response of industrial production to macro stock return volatility, and separately shows that the latter is positively correlated with dispersion in firm-level profit growth.

4. Davis et al. (2006) find that entry cohort effects explain much of the apparent trend increase in the volatility of publicly traded firms. Comin and Mulani (2006) find that sample composition does not explain the trend increase. Comin and Philippon (2005) as well as these two papers measure firm volatility using rolling standard deviations, a measure that differs from ours in ways we explain in Section 2.2.

Our findings are in line with the results in the theoretical models of Bachmann and Bayer (2013) and Chugh (2016) that second-moment shocks account for a small share of macrofluctuations.[5]

We do not present evidence for volatility in stock returns.[6] Since changes in asset returns reflect changes in the price of risk as well as changes in economic fundamentals, economic variables likely imply a cleaner estimate of firm-specific volatility in economic fundamentals.

All our evidence is for firm-level sales and earnings growth. Our results do not directly speak for macro, industry, or plant-level volatility or for volatility in total factor productivity.

As we use publicly traded firms, our evidence does not speak for privately held firms.[7]

Our paper is structured as follows. Section 1 discusses data treatment. Section 2 details our measure of firm-specific volatility and compares it to common dispersion and volatility measures. Section 3 presents our estimates of firm-specific volatility. Section 4 documents volatility trends. Section 5 characterizes the cyclical properties of firm-specific volatility. Section 6 examines the dynamic relation between firm-specific volatility and the macroeconomy. Section 7 concludes.

1. SAMPLE SELECTION AND DATA TREATMENT

We use quarterly data for publicly traded U.S. firms from Compustat to calculate firm-level growth rates in sales and earnings.[8] Our results are based on nominal data. For a subsample for which sector-level producer prices are available, we show in Section 3.2 that results are very similar whether we use nominal or real sales and earnings.

We include only firms that actively trade securities on a U.S. stock exchange or on U.S. over-the-counter (OTC) markets.[9] We exclude firms that trade on U.S. financial

5. Our results point in the same direction as evidence by Gilchrist and Zakrajsek (2012) that the risk premium component of credit spreads is a stronger predictor of real activity than the default risk component. This is because their evidence implies that the mechanism from Christiano, Motto, and Rostagno (2014), whereby firm-specific volatility affects credit spreads through its effect on default risk, is not the main way in which credit spreads affect the economy. Our finding that firm-specific volatility has a small effect on the credit spread is in line with the finding by Levin, Natalucci, and Zakrajsek (2004) that firm-specific volatility does not drive the external finance premium.

6. Papers including Campbell et al. (2001) and Gilchrist, Sim, and Zakrajsek (2014) find that firm-specific volatility in stock returns is countercyclical. Bloom et al. (2014) find that dispersion in U.S. stock returns is countercyclical. The findings of Hamao, Mei, and Xu (2007) suggest that firm-specific volatility in Japanese stock returns may be procyclical.

7. Davis et al. (2006) document volatility trends for privately held as well as publicly traded firms.

8. We use net sales, which is gross sales minus cash discounts, trade discounts, and returned sales and allowances for which credit is given to the customer. Our earnings measure is the variable operating income after depreciation. This is operating income minus the cost of goods sold, fixed costs, and depreciation, but without subtracting net expenditure on interest and taxes.

9. We consider only firms for which Compustat indicates the major exchange or OTC market to be one of the following: the New York Stock Exchange; NYSE Amex; OTC Bulletin Board; NASDAQ-NMS Stock

markets only through American Depositary Receipts (ADRs), and exclude all other firms headquartered outside the United States.

Some firms in Compustat have changed the definition of their fiscal year over the course of data availability. This is reported as a change in the fiscal year-end month. At times, such a change causes double observations for the same firm and quarter. We eliminate double observations by keeping only observations for one fiscal year definition for any firm.[10]

We only consider firms with fiscal years ending in March, June, September, or December. Because of this, every fiscal quarter in our data set corresponds to a single calendar quarter. We plot results in this paper 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:[11]

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

We call this the regular sales growth rate. 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 that is similar to the annual growth rate in Davis et al. (2006):

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

We refer to this as the Davis–Haltiwanger (DH) growth rate. Unlike the regular growth rate, the DH growth rate is symmetric in the sense that DH growth for a decrease in sales from x to a non-negative value y equals the negative of DH growth for an increase from y to x. The DH growth rate is bounded between -200 and 200, unlike the regular growth rate that ranges from -100 to $+\infty$ and therefore does not have an upper bound. In Section 5.1, we discuss the likely implications of the differences between the two growth rates for our results.

Third, we compute earnings growth. Earnings is frequently negative. Therefore, we cannot compute the growth rate in analogy with equation (1). Doing so would yield meaningless results when earnings are negative in t and/or $t-4$. We compute growth in earnings based on the difference in earnings I_{it} in quarter t with

Market; Midwest Exchange (Chicago); Pacific Exchange; Philadelphia Exchange; Other [exchanges]-OTC. Among others, we exclude subsidiaries, consolidated parents, and nontraded companies.

10. For any firm, we keep observations for the fiscal year definition with the highest available number of observations in Compustat quarterly for that firm. We drop firms that happen to have two fiscal year definitions which the firm used for an equally long time and were in use longer than any other fiscal year definition.

11. We drop observations with a negative level of net sales. Negative observations for net sales are plausibly genuine. However, including these observations would complicate the computation of growth rates, while the gain in terms of sample size would be negligible since observations with negative net sales account for a small fraction of observations.

respect to its level four quarters before, divided by the four-quarter lag of net sales:

$$g_{it}^{3} = \frac{I_{it} - I_{i,t-4}}{S_{i,t-4}} * 100. \tag{3}$$

We only compute a growth rate if all levels variables on the right-hand side of the relevant equation are available and nonzero. This implies that we compute growth for continuers only.

Therefore, we do not study entry and exit. Our sample exclusively contains publicly traded firms, which means that it is not appropriate for studying firm births and bankruptcies.[12] A firm that newly appears in our sample was likely in operation before, possibly as a privately held firm. Similarly, a firm that disappears from Compustat does not necessarily enter bankruptcy but may merely be delisting or may be acquired by another firm.

Even if we only consider continuers, entry to and exit from the sample still alters the composition of firms, and could, in principle, affect our volatility measure in that way. However, our measure of firm-specific volatility controls for changes in sample composition. Therefore, entry and exit should not affect our estimates through their effect on sample composition.

We treat unusually large, sudden, and sustained increases in sales as reflecting the effect of a merger or acquisition on the mother firm and treat analogous decreases as reflecting a split. We drop growth rates affected by a merger or split. In this and in all other respects, we treat observations before and after a merger or split as belonging to different firms.[13]

We also drop observations in Compustat quarterly that appear to assign an annual sales or earnings figure to a single quarter, indicated by incidences where either data are available only every four quarters or where an unusually large drop in the recorded level of sales coincides with a switch in reporting frequency from four-quarterly to quarterly.[14]

While data in Compustat quarterly allow for computing four-quarter growth rates from 1962 onward, we perform analysis on growth rates for the period 1978Q1–2012Q4. For earlier years, Compustat contains quarterly data for a substantially smaller number of firms. This suggests that Compustat coverage of publicly traded

12. Similarly, Davis et al. (2006) do not consider entry and exit for their sample of Compustat firms, whereas they do so when they use Census data covering the entire population of U.S. firms.

13. We construct a proxy variable that 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 growth rates for t through $t+3$.

14. We drop a time-t observation if the firm is active at t but is inactive in quarters $t-3$ through $t-1$ and $t+1$ to $t+3$. We also drop a time-t observation when two conditions are fulfilled: the firm is active in t but was inactive in $t-3$ through $t-1$, and the recorded level of sales in t exceeds twice the maximum of sales in quarters $t+1$ through $t+4$. We consider a firm to be inactive when either the firm is not in Compustat at that time, or the firm is in Compustat but both sales and earnings are unavailable or zero.

firms was far from complete at that time, such that any results for those years may not represent the typical publicly traded firm.[15]

For regular sales growth (1) and earnings growth (3), we remove remaining outliers by dropping 5% on either end of the distribution of growth rates over the entire sample period within three-digit North American Industry Classification System (NAICS) sectors for manufacturing firms and within two-digit NAICS sectors for other firms.

One reason for dropping outliers for regular growth rates is that if we were not to, the results in any quarter could be dominated by a single firm with an extremely high positive growth rate since regular growth rates do not have an upper bound. Unlike regular sales growth, the DH sales growth rate (2) is bounded on both ends. We do not drop tail observations for DH growth.

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

In line with common practice, we exclude utilities as well as finance and insurance firms.[16] In addition, we only consider sectors that have at least 15 observations, after dropping tails, in all but a relatively small number of quarters. We do so because our estimator of firm-specific volatility relies on sector-level regressions that involve estimating a time effect for every quarter.

Tables 1 and 2 list the two-digit NAICS sectors and three-digit manufacturing sectors, respectively, that we use. The first column of each table displays the total number of observations by sector for regular sales growth (1) and earnings growth (3) in our cleaned sample.

Treating observations before and after mergers and splits as belonging to different firms, our cleaned sample for 1978Q1–2012Q4 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. Within manufacturing, the following three sectors together account for more than half of observations: computer and electronic product manufacturing, chemical manufacturing, and machinery manufacturing. For DH sales growth, the sample contains 426,754 observations for 12,730 firms.

In Tables 1 and 2, the second column documents the average quarterly number of observations by sector. Estimates for smaller sectors may be less precise, but carry less weight in the estimate of economy-wide firm-specific volatility.

The third column reports an indicator of firm size which we return to in Section 2.

2. ESTIMATION

This section discusses our approach for estimating firm-specific volatility and compares it to common dispersion and volatility measures.

15. In Compustat quarterly without any cleaning apart from eliminating double observations, the number of U.S. firms for which we could compute (regular or DH) sales growth is 18 in 1962Q2, 494 in 1963Q1, has risen to 2,634 by 1978Q1, and is 5,806 on average in 1978Q1–2012Q4.

16. In particular, we exclude NAICS sectors 22 utilities and 52 finance and insurance.

TABLE 1

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

NAICS sector	Total obs	Avg obs	Med sal-GDP * 10^6
21 Mining, quarrying, and oil and gas extraction	20,925	149	10.80
23 Construction	6,837	49	30.63
31–33 Manufacturing	173,968	–	17.23
42 Wholesale Trade	16,138	115	36.09
44–45 Retail Trade	11,636	83	51.37
48–49 Transportation and warehousing	12,481	89	53.73
51 Information	43,470	311	10.53
53 Real estate and rental and leasing	18,505	132	9.08
54 Professional, scientific, and technical services	20,918	149	8.47
56 Administrative and support and waste management and remediation services	10,368	74	18.12
62 Health care and social assistance	9,252	66	15.34
72 Accommodation and food services	9,433	67	17.60
Total	353,931	–	16.76

Note: This table lists the two-digit NAICS sectors in our cleaned Compustat sample for 1978Q1–2012Q4. All statistics are after omitting the top and bottom 5% of the growth distributions by sector, so that the table applies to regular sales growth (1) and earnings growth (3). The samples for Davis–Haltiwanger (DH) sales growth (2) are larger. The first column shows the total number of observations by sector. The second column shows the average quarterly number of observations for every sector for which we run the growth regression (4). The rightmost column shows the median sales-to-GDP ratio by sector multiplied by one million, where we compute any firm's sales-to-GDP ratio as explained in Section 2.1.

TABLE 2

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

NAICS sector	Total obs	Avg obs	Med sal-GDP * 10^6
311 Food manufacturing and 312 beverage and tobacco product manufacturing	8,563	61	63.65
313 Textile mills, 314 textile product mills, and 315 apparel manufacturing	5,787	41	36.85
322 Paper manufacturing	4,150	30	121.25
324 Petroleum and coal products manufacturing	2,756	20	396.46
325 Chemical manufacturing	31,922	228	9.82
326 Plastics and rubber products manufacturing	5,207	37	22.28
331 Primary steel manufacturing	5,694	41	75.12
332 Fabricated metal product manufacturing	7,938	57	27.88
333 Machinery manufacturing	17,817	127	17.84
334 Computer and electronic product manufacturing	53,825	384	8.67
335 Electrical equipment, appliance, and component manufacturing	7,490	54	22.98
336 Transportation equipment manufacturing	9,909	71	61.46
339 Miscellaneous manufacturing	12,910	92	8.09
Total manufacturing	173,968	–	17.23

Note: This table lists the three-digit NAICS sectors within manufacturing in our cleaned Compustat sample for 1978Q1–2012Q4. Guided by data availability, we treat NAICS sectors 311 and 312 as a single sector, and similarly combine NAICS sectors 313, 314, and 315. Other notes are as under Table 1.

2.1 Our Method

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

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

We obtain the residuals ε_{it} from separate regressions of equation (4) by three-digit NAICS sector for manufacturing firms, and by two-digit NAICS sector for other firms.

γ_{it} represents net sales growth or earnings growth for firm i as defined in equations (1)–(3). The constant is c. By including firm fixed effects a_i, we control for any firm i's typical growth rate over the sample period. By including time effects b_t, we control for the typical growth rate in quarter t of firms in the same sector.

We capture firm size by dummy variables e_{dt} that indicate whether in any quarter, a firm belongs to a particular decile in the distribution of sales-to-GDP ratios for the relevant sector over the entire sample period. To ensure that the sales-to-GDP ratios do not reflect seasonal factors, we use 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 $t-3$ through t.

The rightmost columns in Tables 1 and 2 list the median sales-to-GDP ratio by sector in our cleaned sample, after multiplying the ratios by one million. The median sales-to-GDP ratio varies substantially across sectors for firms included in the sample. In this respect, note that our size variable e_{dt} captures within-sector variation in firm size. Therefore, this size variable captures independent information from the time effects b_t that account for sector-level growth.

In summary, the residuals ε_{it} from regression (4) capture the extent to which a firm's growth in a quarter is atypical given the firm's typical growth rate over the estimation period, given the typical growth rate 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.

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.[17]

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:

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

17. Equation (5) is the firm-level equivalent of McConnell and Perez-Quiros's (2000) formula for the volatility of aggregate output growth. If ε_{it} is distributed $N(0, \sigma^2_{\varepsilon,it})$, equation (5) yields an unbiased estimator $\widehat{\sigma}_{\varepsilon,it}$ of the true standard deviation $\sigma_{\varepsilon,it}$. The proof is as follows. 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 $\varepsilon_{it} \sim N(0, \sigma^2_{\varepsilon,it})$, then $|\varepsilon_{it}|$ is half-normally distributed with $E(|\varepsilon_{it}|) = \sqrt{2/\pi}\sigma_{\varepsilon,it}$. Combining the two foregoing equations yields $E(\widehat{\sigma}_{\varepsilon,it}) = \sigma_{\varepsilon,it}$.

We run regression (6) for the entire economy as well as for the manufacturing sector. 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}. In Section 3, we plot the time path of $\widehat{\beta_t}$ to uncover the evolution of firm-specific volatility.[18]

Because we include firm fixed effects in equations (4) and (6), our approach controls for changes in sample composition both regarding the typical growth rate of a firm and regarding the typical level of volatility of a firm. Changes in sample composition could otherwise affect measured trends or cycles in volatility, as the following examples illustrate.

First, to the extent that it has become easier for comparatively risky firms to list on the U.S. stock market,[19] not controlling for sample composition in equation (6) would bias our results toward finding a trend increase in firm-specific volatility.

Second, the ability for comparatively volatile firms to issue publicly traded securities may be procyclical, in which case not controlling for sample composition would bias our results toward finding procyclical firm-specific volatility.

Third, the share of publicly traded U.S. firms for which Compustat provides quarterly data likely expanded even over the course of our sample period, which would bias our results toward finding a trend increase in volatility if firms that are covered at a later date tend to be more volatile. Such could be the case if the database tends to cover larger firms at an earlier date than smaller firms.

Fourth, expansion in Compustat coverage can also affect the cyclical properties of estimated firm-specific volatility. For instance, in 1982, there is a pronounced increase in the number of firms in Compustat, which for the most part reflects the appearance of a substantial number of Nasdaq and OTC firms in the database.[20] To the extent that Nasdaq and OTC firms are more volatile than other publicly traded firms, this would tend to imply an increase in measured firm-specific volatility if we were not to control for sample composition. Since this particular change in composition happens during the 1981–1982 recession, it would tend to bias the results toward finding countercyclical firm-specific volatility if we were not to control for it.

2.2 Relation to Common Dispersion and Volatility Measures

We now compare our measure from Section 2.1 to common dispersion and volatility measures. We first compare it to measures for dispersion in the distribution of firm-level growth rates such as the cross-sectional IQR and the cross-sectional standard deviation, which Bloom (2009) and Bloom et al. (2014) use.

18. We omit the time effect for the first quarter. We plot the constant reported in the Stata within-regression `xtreg,fe` for the first quarter, and the sum of this constant and the time effect for any other quarter.

19. See Fama and French (2004), Brown and Kapadia (2007), and Fink et al. (2010).

20. In our cleaned sample, the number of firms for which we could compute regular sales and earnings growth increases from 942 to 1,693 from 1981Q4 to 1982Q4, an increase by 751 firms that is mostly accounted for by an increase by 529 in the number of firms that Compustat indicates as trading either on the OTC Bulletin Board or on the Nasdaq-NMS stock market. The latter figure does not include the increase by 133 in the number of firms in the residual category Other-OTC over the same time frame.

First, our measure aims to estimate firm-specific volatility more cleanly than dispersion measures do. Measures of cross-sectional dispersion filter out aggregate variation and are therefore a natural proxy for volatility originating from shocks to individual firms. However, cross-sectional dispersion reflects a range of reasons for cross-firm differences in growth rates besides firm-specific shocks. These reasons include sector-level shocks, firm-specific or sector-level trends, as well as systematic differences in growth rates for firms of a different size.

In our growth regression (4), we control for firm-specific trend growth by including firm fixed effects a_i.[21] By including time effects b_t in that sector-level regression, we control for sector-level factors. Size dummies e_{dt} control for differences in growth rates across firms of different size.

Because we control for a wider range of factors than dispersion measures do, we argue that our measure yields a cleaner estimate of firm-specific volatility.

Second, dispersion measures do not control for changes in the composition of the sample of firms. In an effort to reduce the influence of changes in sample composition, Bloom (2009) and Bloom et al. (2014) compute dispersion using samples restricted to firms with a minimum of available observations. This implies restricting the sample to a particular type of firms that may not be representative, while there may still be considerable changes in composition which the measure does not control for.

As we control for changes in composition by including firm fixed effects in our firm-level regressions (4) and (6), we do not impose any restriction on the degree to which the composition of the sample changes over time.

Appendix A shows that a variant of the estimation framework in equations (4)–(6) is equivalent to computing cross-sectional standard deviations by sector. Relative to this variant, our measure adds firm fixed effects and size controls to the growth rate regression and firm fixed effects to the volatility regression. As we just explained, these features help us to obtain a cleaner estimate of firm-specific volatility that controls for sample composition.

Next, we compare our measure to rolling standard deviations, which Comin and Philippon (2005), Comin and Mulani (2006), and Davis et al. (2006) use to characterize trends in firm-level volatility.

First, rolling standard deviations reflect all reasons for deviations in a firm's growth rate from its average over the relevant time window. These include macroeconomic, sectoral, and firm-specific reasons for variation in firm-level growth rates.

Since we run our growth rate regression (4) by sector and include time effects, we control for macroeconomic and sector-level factors, as we aim to estimate the component of variation in firm-level growth rates that is specific to the firm.

Second, rolling standard deviations estimate average firm-level volatility in consecutive time windows, but do not yield separate estimates for volatility in individual quarters. Therefore, that measure does not indicate the precise timing of changes in volatility.

21. By entering firm fixed effects, we control for time-invariant firm-specific trend growth. In a comparable regression, De Veirman and Levin (2012) control for time-varying firm-specific trends by entering Hodrick–Prescott (HP) trends of firm-level growth instead.

Our estimator $\widehat{\beta_t}$ from equation (6) captures firm-specific volatility in a particular quarter, and therefore precisely indicates the timing of changes in volatility. Therefore, we use the same measure to characterize the trend and cyclical properties of firm-specific volatility.

Third, computing rolling standard deviations requires omitting observations that are not part of a spell of available data that is long enough for it to cover at least one time window. This requirement is akin to the above-mentioned restriction to firms with a minimum of available observations and similarly raises a selection issue. Our estimator does not imply such a restriction.

3. ESTIMATED FIRM-SPECIFIC VOLATILITY

This section presents our estimates of firm-specific volatility. Section 4 performs further analysis regarding volatility trends, while Sections 5 and 6 document the cyclical properties of firm-specific volatility.

3.1 Patterns in Firm-Specific Volatility

Figure 1 shows firm-specific volatility estimated using equations (4)–(6). Volatility for all firms in our cleaned Compustat sample is in the top row, while firm-specific volatility for the manufacturing sector is in the bottom row. From left to right, the columns pertain to volatility in regular sales growth (1), volatility in DH sales growth (2), and volatility in earnings growth (3). The figures plot volatility along with 95% confidence intervals based on heteroskedasticity-robust standard errors. In this figure as in other figures below, vertical shaded areas indicate National Bureau of Economic Research (NBER) recessions. Units are percentages in the sense that the level of 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 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 sales and earnings growth rates but not so for DH sales growth.[22] In Sections 5 and 6, we will specify volatility in percent deviations from trend, in which case the units are comparable across variables.

Figure 1 plots volatility before seasonal adjustment. The top right panel of Figure 1 reveals a pronounced seasonal pattern in earnings volatility, 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 5 and 6 are based on seasonally adjusted firm-specific volatility.

22. We compute earnings growth (3) 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 earnings growth, and therefore may explain why earnings growth volatility is always lower than volatility in either of the two sales growth measures in Figure 1. 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 the fact that measured DH sales growth volatility is always above measured regular sales growth volatility in Figure 1.

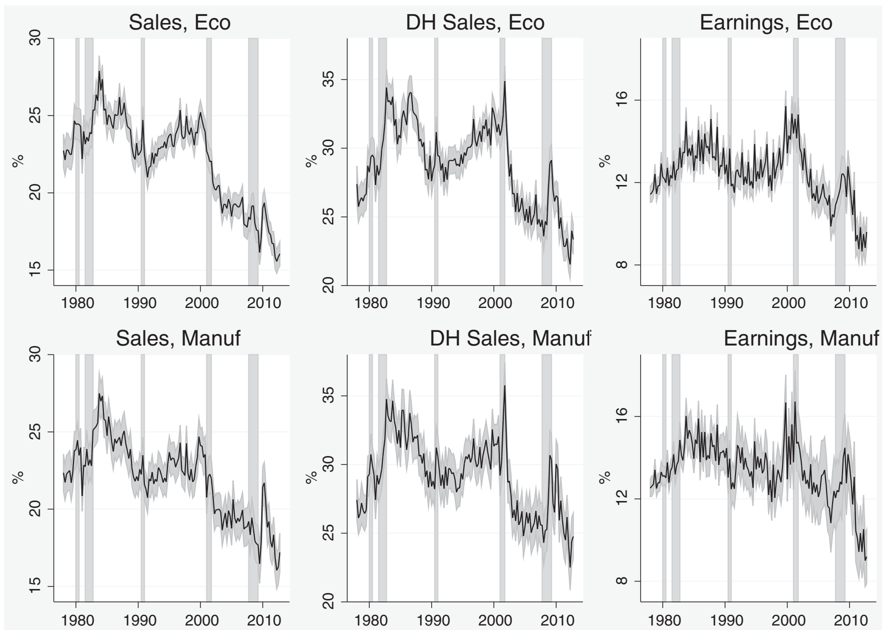

FIG. 1. Firm-Specific Sales and Earnings Volatility: Economy and Manufacturing.

NOTE: This figure shows firm-specific volatility estimated using equations (4)–(6), along with 95% confidence intervals based on heteroskedasticity-robust standard errors. The top row shows results for the overall economy, while the bottom row does so for the manufacturing sector. From left to right, volatility is in regular sales growth (1), Davis–Haltiwanger (DH) sales growth (2), and earnings growth (3). Sales and earnings are nominal. Units are percentages, in the sense that the level of 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. Vertical shaded areas indicate NBER recessions.

We draw three lessons from the panels in the top row of Figure 1.

First, there is some evidence for a trend decline in firm-specific volatility, driven by a pronounced decline in volatility in the early 2000s. For any of the three growth rates, a typical firm is more stable toward the end of the sample than at any other time in the sample period. We return to this finding in Section 4.

Second, firm-specific volatility tends to increase during recessions, but these increases are moderate. This observation applies to the Great Recession of 2007–2009. Seasonally adjusted firm-specific volatility in DH sales growth rises by 17.03% from the quarter before the 2007Q4–2009Q2 recession to its peak in 2009Q1. There is a similar percent increase in earnings volatility over the same time frame, while the increase in regular sales growth volatility during the 2007–2009 recession is smaller and shorter lived.

Figure 1 indicates that the increase in firm-specific volatility during the Great Recession was not sufficient to offset the downward volatility trend. For all three growth rates, volatility remained below the levels it attained in the late 1990s.

During the Great Recession, firm-specific volatility never substantially exceeds its sample mean. For DH sales growth, seasonally adjusted volatility is 0.08 standard deviations above its sample mean at its peak during the Great Recession. Earnings volatility similarly peaks near its sample mean. For regular sales growth, volatility remains well below its sample mean throughout the Great Recession.

Third, recessions appear to mark turning points between periods with increasing and decreasing volatility. Firm-specific volatility increases during the recessions of the early 1980s. It then decreases until the 1990–1991 recession. Subsequently, it increases until the 2001 recession. It then decreases until the 2007–2009 recession. We provide a tentative economic explanation for these medium-run patterns when we conclude the paper in Section 7.

As the bottom row of Figure 1 documents, results for the manufacturing sector are similar. A noteworthy difference is that after the NBER-dated 2007–2009 recession, volatility in regular sales growth increases by more in the manufacturing sector than in the whole economy.

3.2 Robustness: Real Growth Rates

Estimated firm-specific volatility in Figure 1 is for nominal sales and earnings growth. Furthermore, the estimate is based on growth regressions (4) by three-digit NAICS sector for manufacturing firms and by two-digit NAICS sector for other firms. In this context, it is, in principle, possible that changes in relative prices within two- or three-digit sectors affect our estimates of firm-specific volatility. For instance, when prices in a six-digit NAICS sector increase relative to prices of other six-digit sectors in the same broader sector, all other things equal this implies that nominal sales of firms in that six-digit sector increase relative to the average in the broader sector. This could affect estimated firm-specific volatility even if quantities produced did not change.

We therefore check for robustness with respect to deflating firm-level nominal sales and earnings by the Producer Price Index (PPI) specific to the six-digit NAICS sector to which the relevant firm belongs. To this end, we use a subset of our cleaned Compustat sample for which data on six-digit PPIs are available from the Bureau of Labor Statistics.

The requirement of having a six-digit PPI available substantially reduces the number of observations, especially in earlier years and for nonmanufacturing firms. So as to ensure that there are at least 12 observations in all but a few quarters for every sector in the sample, we restrict the sample to 1986Q1–2012Q4 for this purpose, and drop all nonmanufacturing sectors as well as three of the three-digit manufacturing sectors listed in Table 2.[23]

23. The three manufacturing sectors which we drop for this purpose are the joint sector 313 textile mills, 314 textile product mills, and 315 apparel manufacturing, as well as the sectors 322 paper manufacturing and 326 plastics and rubber products manufacturing. The remaining sample of 10 manufacturing sectors has 100,582 observations for regular sales and earnings growth and 121,244 for DH sales growth.

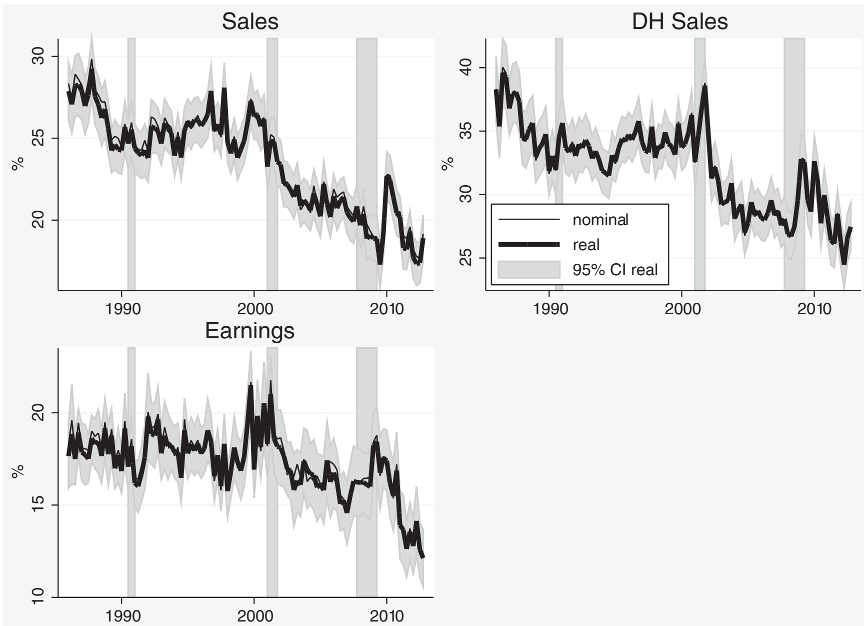

FIG. 2. Firm-Specific Volatility in Nominal versus Real Growth Rates.

NOTE: For a subsample for which we could compute real sales and earnings, this graph shows that firm-specific volatility is similar whether we use real or nominal growth rates. Bold lines pertain to firm-specific volatility in real sales and earnings growth. Thin lines indicate volatility in nominal growth rates. The confidence intervals are 95% confidence bands for volatility in real growth rates based on heteroskedasticity-robust standard errors. To compute real variables, we deflate nominal sales and earnings by the PPI at the six-digit NAICS level. The figure shows firm-specific volatility for the restricted manufacturing sector in 1986Q1–2012Q4 estimated using equations (4)–(6). More details are in Section 3.2. "Sales" indicates firm-specific volatility in regular sales growth (1); "DH sales" in DH sales growth (2); and "Earnings" in earnings growth (3). Vertical shaded areas indicate NBER recessions. Units are as in Figure 1.

We use equations (4)–(6) to estimate firm-specific volatility in real sales and earnings growth for this sample.

The bold lines in Figure 2 indicate firm-specific volatility in real sales and earnings growth. The thin lines indicate firm-specific volatility in nominal growth rates for the same sample. Confidence intervals are 95% confidence bands around estimated volatility in real growth.

We find that for this subsample of manufacturing firms, firm-specific volatility in real sales and earnings growth is very similar to volatility in nominal growth, to the point that the two lines are hard to distinguish. Volatility in nominal growth is always contained within the 95% confidence band around volatility in real growth. The similarity suggests that differences in price changes across sectors do not have a substantial effect on our estimates of firm-specific volatility. We use nominal sales and earnings in the remainder of the paper.

4. TRENDS IN FIRM VOLATILITY

In this section, we reconcile earlier evidence for a trend increase in firm volatility with our finding from Section 3.1 that a typical publicly traded firm has become more stable. In so doing, we examine the effect of changes in sample composition on volatility trends.

Comin and Philippon (2005), Comin and Mulani (2006), and Davis et al. (2006) document a trend increase in 10-year rolling standard deviations of sales or employment growth of publicly traded U.S. firms covered by Compustat.

The latter two papers investigate the effects of sample composition. Comin and Mulani (2006) conclude that the trend increase is not driven by changes in sample composition. Davis et al. (2006) ascribe much of the trend increase to an increase in the fraction of volatile firms as it has become easier for comparatively risky firms to list publicly in the United States.

Both studies use regressions with 10-year rolling standard deviations as the dependent variable to gauge the effect of changes in sample composition.[24] This rolling windows measure is not likely to be ideal for the purpose of assessing the effect of annual or quarterly changes in composition. In particular, it requires that the sample be restricted to observations that are part of a spell of at least 10 years of available data. Therefore, the analysis necessarily abstracts from changes in composition that involve short spells of data availability. In that our measure of firm-specific volatility does not require such a restriction, changes in the composition of our sample more closely reflect actual changes in the composition of publicly traded firms.

Before showing evidence with our quarterly volatility measure, we replicate the above-mentioned findings of a trend increase in the volatility of publicly traded firms by computing rolling standard deviations on our cleaned Compustat sample. In particular, we compute firm volatility σ_t^{roll} assigned to quarter t as the cross-sectional average of firm-level rolling standard deviations σ_{it}^{roll}:

$$\sigma_t^{roll} = \frac{1}{N_t} \sum_{i=1}^{N_t} \sigma_{it}^{roll}, \tag{7}$$

where N_t is the number of firms for which a rolling standard deviation exists in quarter t, and where σ_{it}^{roll} is the centered 40-quarter firm-level rolling standard deviation:

$$\sigma_{it}^{roll} = \sqrt{\frac{1}{39} \sum_{\tau=-19}^{20} (\gamma_{i,t+\tau} - \overline{\gamma}_{it})^2}, \tag{8}$$

24. Comin and Mulani (2006) regress rolling standard deviations on firm fixed effects, firm size, and age. Davis et al. (2006) emphasize a regression with rolling standard deviations as the dependent variable and cohort effects as one of the regressors, where cohorts reflect the time of a firm's first listing.

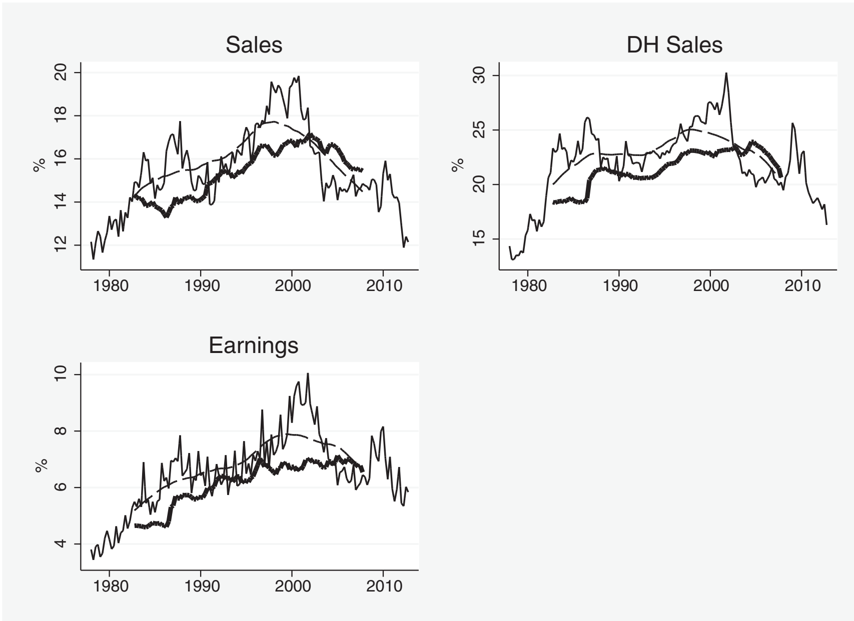

FIG. 3. Rolling Standard Deviations versus Firm-Specific Volatility.

NOTE: This figure shows a trend increase in rolling standard deviations and our quarterly measure of firm-specific volatility when neither measure controls for changes in sample composition regarding a firm's typical volatility. The bold lines plot the cross-sectional average of centered 40-quarter rolling standard deviations for sales and earnings growth from equations (7) and (8). The thin solid lines are estimates of firm-specific volatility using equations (4) and (5) as well as a variant of the volatility regression, equation (6), that does not include firm fixed effects. The long dashed lines are centered 40-quarter averages of these estimates of firm-specific volatility. All results in this graph are for observations that are part of a firm-level spell of at least 40 consecutive quarters of available observations in our cleaned Compustat sample. Figure headings are in analogy with Figure 2.

where $\overline{\gamma}_{it} = (1/40)\sum_{\tau=-19}^{\tau=20} \gamma_{i,t+\tau}$. The division through 39 in equation (8) reflects a degrees-of-freedom correction.[25]

In computing rolling standard deviations, we do not control in any way for changes in sample composition. The bold line in Figure 3 reveals a gradual increase in the rolling standard deviation σ_t^{roll} for most of the sample period.[26] For regular sales growth, the standard deviation increases from 14.33 to 17.18, an increase by 19.83%,

25. Since computing a 40-quarter standard deviation requires a growth rate to be available for 40 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 DH growth rates and 130,303 observations for 1,937 firms in the case of regular sales and earnings growth rates. As we explain in Section 2, we drop tail observations for the latter two growth rates, which implies substantially fewer periods with 40 or more consecutive quarters of observations.

26. Figure 3 does not plot recession bars. In keeping with the explanation in Section 2.2, 40-quarter rolling standard deviations indicate average volatility over a 40-quarter window but do not indicate the precise timing of changes in firm-level volatility. We therefore do not examine how this measure comoves with the business cycle.

from the 40-quarter window centered in 1982Q4 (the beginning of the sample) to the window centered in 2002Q1. For DH sales growth, the increase over the same time frame is 26.15%, while for earnings growth it is 51.28%.

While Comin and Philippon (2005), Comin and Mulani (2006), and Davis et al. (2006) document a trend increase in 10-year rolling standard deviations for publicly traded firms on annual data from the 1950s onward, they find that the upward trend continues after 10-year windows centered in 1982. We just replicated the latter part of their findings on our cleaned quarterly data set. In addition, we showed that the trend increase continues for a few more years after the end of their sample periods.

More recently, the upward trend in sales growth volatility for publicly traded firms seems to have been reversed. Volatility is highest in 40-quarter windows centered in about 2002, and declines through the end of our sample at windows centered in 2007Q4. However, the apparent reversal is too short to allow for a comparison of two separate 40-quarter windows. Rolling standard deviations indicate no trend reversal for earnings growth volatility.

We now return to our finding from Section 3.1, plotted in the top row of Figure 1, that firm-specific volatility of a typical publicly traded firm is substantially lower at the end of our sample period than at other times. Recall that those estimates control for changes in sample composition through the inclusion of firm fixed effects in the growth regression (4) as well as in the volatility regression (6).

Figure 3 reconciles that finding with earlier findings of a trend increase. The thin solid line in Figure 3 plots our estimates of firm-specific volatility using equations (4)–(6) after omitting firm fixed effects from the volatility equation (6). This measure does not control for changes in sample composition regarding individual firms' typical level of volatility, a feature which it shares with rolling standard deviations. To further enhance comparability, we compute this measure using only observations that are part of a continuous spell of at least 40 available growth rate observations. The long dashed lines in Figure 3 are centered 40-quarter moving averages of this quarterly measure of firm-specific volatility. For the moving average, the value assigned to quarter t is the average of firm-specific volatility from $t-19$ to $t+20$.

The moving averages of quarterly firm-specific volatility gradually increase for much of the sample period. In this case, the upward trend is reversed for all three variables, and the highest levels occur somewhat earlier than we found above for rolling standard deviations. For regular sales growth, volatility is highest in the window centered in 1998Q1. From the beginning of the sample until that window, the rolling average of firm-specific volatility in regular sales growth increases by 23.89%. Over the same time frame, volatility increases by 25.14% for DH sales growth and by 49.76% for earnings growth.

Therefore, rolling standard deviations and our method imply similar trend changes in volatility when we do not control for changes in sample composition regarding a firm's typical level of volatility.

When we do include firm fixed effects in the volatility regression (6), there is no upward trend in firm-specific volatility in the 1980s and 1990s, whether we use our full sample as in Figure 1 or whether we use the sample restricted to observations that are part of a continuous spell of at least 40 quarters of available observations.

This indicates that the trend increase in the volatility of publicly traded firms in the 1980s and 1990s in Figure 3 is driven by changes in sample composition. This likely reflects the fact that increasingly risky firms have listed publicly, as mentioned by Davis et al. (2006) and as documented by Fama and French (2004), Brown and Kapadia (2007), and Fink et al. (2010). It plausibly also reflects expansion of Compustat coverage of quarterly data for publicly traded firms, especially earlier on in our sample.[27]

5. FIRM VOLATILITY AND THE BUSINESS CYCLE

This section documents the contemporaneous relation of firm-specific volatility with the business cycle, and reconciles our results with earlier findings based on dispersion measures. We examine the dynamic relation between firm-specific volatility and real activity in Section 6.

5.1 Cyclical Properties of Firm-Specific Volatility

The top row of Figure 4 plots firm-specific volatility for the overall economy after seasonal adjustment and after detrending the seasonally adjusted series by computing the percent deviation from its Hodrick-Prescott (HP) trend with smoothing parameter 16,000.[28] From left to right, panels pertain to volatility in regular sales growth, in DH sales growth, and in earnings growth.

The graphs indicate that detrended firm-specific volatility tends to peak during or around the time of recessions. Around the time of the recessions of 1981–1982, 2001, and 2007–2009, volatility peaks at numbers ranging from 8% to 16% above trend. These peaks do not necessarily occur during the recession, but virtually always occur within four quarters before the beginning and four quarters after the end of the recession.

Volatility also peaks three to five quarters before the stock market crash of 1987Q4 at 7% to 9% above trend. This episode is not associated with a recession. In most cases, small and short-lived increases in detrended volatility occur in the two other remaining recessions in the sample: 1980 and 1990–1991.

27. As we mention at the end of Section 2.1, many firms that are plausibly volatile newly appeared in Compustat quarterly in 1982. This plausibly accounts for the pronounced increase, in Figure 3, in rolling standard deviations for DH sales growth and earnings growth from the window centered in 1986Q3 to that centered in 1987Q3.

28. We implement multiplicative X12 seasonal adjustment for all three growth rate measures. The smoothing parameter of 16,000 implies a relatively rigid trend. Our main conclusions from Sections 5 and 6 are robust to using a smoothing parameter at the standard setting of 1,600.

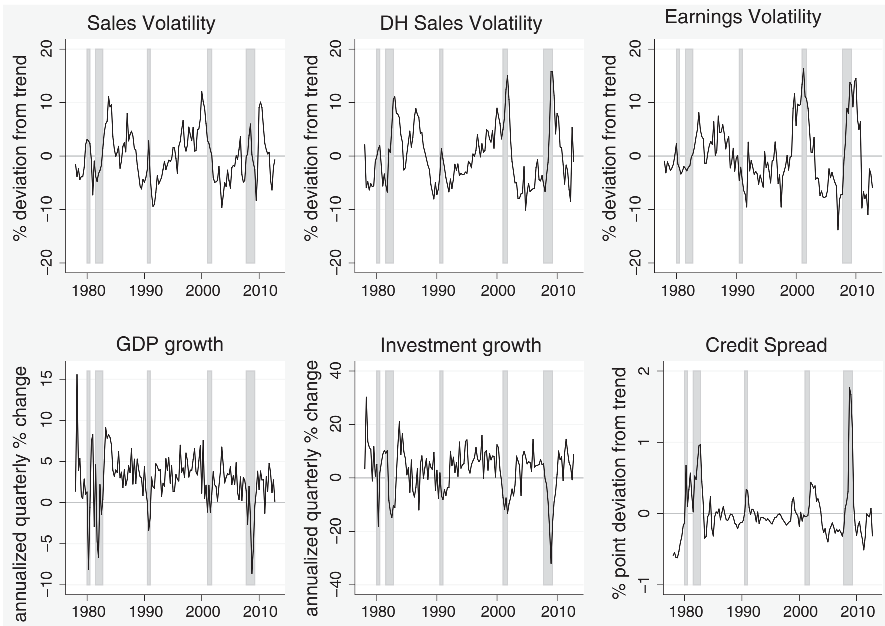

FIG. 4. Detrended Firm-Specific Volatility, Real Activity Growth, Detrended Credit Spread.

NOTE: The top row shows, from left to right, detrended firm-specific volatility in regular sales growth (1), DH sales growth (2), and earnings growth (3). These are the series in the top row of Figure 1 after seasonally adjusting and then detrending the seasonally adjusted series by computing the percentage difference from a Hodrick–Prescott (HP) trend with smoothing parameter 16,000. Detrended firm-specific volatility tends to peak within four quarters before the beginning and four quarters after the end of a recession. 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 detrended 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 HP trend with smoothing parameter 16,000.

In the remainder of this subsection, we examine the cyclical properties of firm-specific volatility by means of regressions on recession indicators and correlations with GDP growth.

The top left part of Table 3 shows results from regressions of detrended firm-specific volatility on a constant and a recession indicator that equals one if the economy is in recession according to the NBER business cycle reference dates and zero otherwise. In this table as well as in Table 4 below, "Sal." indicates regular sales growth, "DH" stands for Davis–Haltiwanger sales growth, and "Earn." indicates earnings growth.

We use Newey–West standard errors to correct for substantial serial correlation in the residuals and to correct for any heteroskedasticity.

For regular sales growth, we find that, on average, detrended firm-specific volatility is about the same during recessions as at other times. For DH sales growth and earnings growth, volatility is moderately higher during recessions than at other times, but the difference is not statistically significant at the 5% level. For DH sales growth,

TABLE 3

FIRM-SPECIFIC VOLATILITY: CYCLICAL PROPERTIES

	Regression on recession dates			Correlation	
	constant	rec	$\overline{R^2}$	gdpg1	gdpg4
Economy					
Sal.	−0.08 (0.84)	0.23 (1.14)	−0.01	0.11	0.28**
DH	−0.65 (0.88)	3.53 (1.99)	0.05	−0.09	−0.23**
Earn.	−0.67 (0.90)	3.67 (2.30)	0.05	−0.04	−0.11
Manufacturing					
Sal.	0.15 (0.87)	−1.13 (1.23)	0.00	0.16	0.33**
DH	−0.58 (0.84)	3.20 (2.01)	0.04	−0.05	−0.18*
Earn.	−0.55 (0.93)	3.04 (2.26)	0.02	0.01	−0.07

NOTE: This table documents that our measure of firm-specific volatility is at most moderately countercyclical. The top half of the table pertains to firm-specific volatility for the overall economy and the bottom half to firm-specific volatility for the manufacturing sector. Rows labeled "Sal." pertain to firm volatility in regular sales growth (1), rows labeled "DH" to volatility in Davis–Haltiwanger (DH) sales growth (2), and rows labeled "Earn." to volatility in earnings growth (3). The left part of the table pertains to regressions of detrended firm-specific volatility on a constant and "rec", a variable that is one when the economy is in recession according to the NBER business cycle dates and zero otherwise. Newey-West standard errors are in brackets. 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 four-quarter percentage change in real GDP. Data are cleaned as explained in Section 1 and firm-specific volatility is detrended as explained below Figure 4. The sample is 1978Q1–2012Q4. ** and * indicate significance at the 1% and 5% levels, respectively.

volatility is 2.88% above trend in recessions and 0.65% below trend at other times, such that the difference is 3.53 percentage points.

The adjusted R^2s from these regressions are very low, which indicates that recessions explain a very small fraction of fluctuations in detrended firm-specific volatility.

The top right part of Table 3 shows the contemporaneous correlations of detrended economy-wide firm-specific volatility with real GDP growth. The column labeled "gdpg1" pertains to annualized quarterly GDP growth and the column labeled "gdpg4" to four-quarter GDP growth. The former is a common way of computing output growth, while the latter is in analogy with the fact that our firm-specific volatility measures are based on four-quarter firm-level growth rates.

Correlations with quarterly GDP growth are fairly small and not statistically significant. For four-quarter GDP growth, the correlation with volatility in regular sales growth is 0.28, while that with DH sales growth is −0.23, both correlations being significant at the 1% level.

As the bottom half of Table 3 reveals, regression results and correlations are similar for firm-specific volatility in the manufacturing sector.

Overall, the results from Table 3 paint a mixed picture as to whether firm-specific volatility is countercyclical. Since most evidence is statistically insignificant, the results suggest that the association with the business cycle is not particularly strong. The only significant results in Table 3 are the correlations of regular and DH sales growth with four-quarter GDP growth, but these correlations have opposite signs.

Part of this difference in correlations reflects the fact that in the recessions of 2001 and 2007–2009, detrended volatility in DH sales growth peaks when four-quarter

TABLE 4

CROSS-SECTIONAL DISPERSION: CYCLICAL PROPERTIES

		Regression on recession dates				Correlation	
		constant	rec	trend	$\overline{R^2}$	gdpg1	gdpg4
Standard Deviation							
Sal.	dc	0.05 (1.41)	−1.10 (2.25)	N/A	0.00	0.13	0.25**
DH	dc	−0.90 (1.39)	4.17 (3.57)	N/A	0.02	−0.03	−0.18*
Earn.	dc	−0.21 (2.31)	−0.67 (5.01)	N/A	−0.01	0.11	0.19*
Interquartile Range							
Sal.	/	14.86** (1.17)	2.84** (0.93)	0.03** (0.01)	0.28	−0.27**	−0.40**
Sal.	d	−1.98 (1.51)	10.42** (3.42)	N/A	0.10	−0.24**	−0.37**
Sal.	dc	−1.39 (1.61)	7.43** (2.54)	N/A	0.07	−0.09	−0.18*
DH	/	12.78** (1.01)	3.16** (0.83)	0.04** (0.01)	0.37	−0.30**	−0.50**
DH	d	−2.60 (1.66)	13.97** (3.82)	N/A	0.13	−0.26**	−0.49**
DH	dc	−2.66 (1.86)	14.28** (5.38)	N/A	0.13	−0.19*	−0.43**
Earn.	dc	−1.73 (1.66)	9.18* (4.10)	N/A	0.08	−0.17*	−0.22*

NOTE: The top part of the table shows that the cross-sectional standard deviation is at most moderately countercyclical. The bottom part replicates the finding by Bloom et al. (2014) that the cross-sectional interquartile range (IQR) is countercyclical and documents that the same applies when we implement similar cleaning and detrending as we did for our measure of firm-specific volatility in Table 3. The left part of the table shows the results from regressions of the cross-sectional standard deviation or the IQR on recession dates, while the right part shows correlations with GDP growth. For nondetrended IQRs, we include a linear trend ("trend") in the regressions on a recession indicator. For rows labeled "/", we do not detrend the IQR and do not implement the data cleaning of Section 1. For rows labeled "d", we use the same sample but detrend the IQR by computing the percentage difference from an HP trend with smoothing parameter 16,000. For rows labeled "dc", we detrend the standard deviation or IQR and clean the data as explained in Section 1. Other row and column labels are as defined under Table 3. All results in this table are for long-lived firms as defined in Section 5.2. The sample period is 1963Q1–2012Q4 for noncleaned samples and 1978Q1–2012Q4 for cleaned samples. ** and * indicate significance at the 1% and 5% levels, respectively.

GDP growth is near its trough, while volatility in regular sales growth is close to or below trend.

A more general explanation for the difference in results for regular and DH sales growth is based on the mathematical relation between the two growth rates. Appendix B shows that the DH growth rate (2) is a sign-preserving, strictly concave function of the regular growth rate (1). As for positive firm-level growth rates, the function is such that it translates regular growth rates on the interval $(0, +\infty)$ to DH growth rates on the interval $(0, 200]$, preserving the ordering of the growth rates but condensing the distribution. On the other hand, the function stretches out the distribution of negative regular growth rates $[-100, 0)$ to DH growth rates on the interval $[-200, 0)$, again preserving the ordering of growth rates.

Therefore, if all firms in the economy were to have positive growth, the DH growth rate would indicate smaller differences across firms than the regular growth rate. Conversely, if all firms were to shrink, the DH growth rate would indicate larger differences. Our intuition is that this implies that relative to regular growth, the DH growth rate indicates less variation in growth in booms but indicates more variation in recessions. If so, that suggests that the DH growth rate is by construction more likely to indicate countercyclical firm-specific volatility.

So as not to understate the case for countercyclicality, we pay particular attention to the results with DH sales growth. With that growth rate, we find that the correlation between firm-specific volatility and quarterly GDP growth is −0.09 and not significantly different from zero, while the correlation with four-quarter GDP growth is −0.23 and significant. Still with DH growth, detrended firm-specific volatility is moderately higher in recessions than at other times, but that difference is not statistically significant.

Therefore, even with DH sales growth, the case for countercyclicality in firm-specific volatility is far from overwhelming. Our assessment is that firm-specific volatility in DH sales growth is moderately countercyclical.

5.2 Cyclical Properties of Dispersion

In this subsection, we replicate evidence from Bloom et al. (2014) that the IQR is countercyclical, and show that it is more strongly countercyclical than our measure of firm-specific volatility when we apply similar data processing for both measures. Before doing so, we show that the cross-sectional standard deviation has similar cyclical properties as our measure of firm-specific volatility has.

The top part of Table 4 shows results for the cross-sectional standard deviation in regular sales growth, DH sales growth, and earnings growth on our cleaned Compustat sample. In analogy with our measure of firm-specific volatility, we detrend the seasonally adjusted cross-sectional standard deviation by computing the percent difference from its HP trend with smoothing parameter 16,000.[29] In this case, however, we restrict the sample to long-lived firms as we explain below for the IQR.

The results are mixed: with regular sales and earnings growth, the cross-sectional standard deviation is mildly procyclical, while it is mildly countercyclical with DH sales growth. Focusing on DH sales growth, the cross-sectional standard deviation is moderately higher during recessions than at other times but that difference is not statistically significant. The correlation with quarterly GDP growth is near zero and insignificant, while the correlation with four-quarter GDP growth is −0.18 and significant at the 5% level.

These results are quite similar to those with our measure of firm-specific volatility in Table 3.

The remainder of Table 4 documents the cyclical properties of the IQR. For regular and DH sales growth, we first replicate the result from Bloom et al. (2014) that the IQR in sales growth is countercyclical. Rows marked "/" pertain to a sample which we mean to be comparable to theirs. In this case, we do not implement the cleaning described in Section 1 apart from selecting U.S. firms and eliminating double observations.[30] The sample period is 1963Q1–2012Q4.[31] Like Bloom et al. (2014),

29. We seasonally adjusted all series for the cross-sectional standard deviation and for the IQR underlying the results in Table 4 using multiplicative X12 seasonal adjustment.

30. In this sample, we include firms with any U.S. exchange code, irrespective of whether they actively trade securities on a stock exchange or on OTC markets. We exclude ADRs and all other firms headquarted outside the United States. We eliminate double observations by keeping only observations for the single longest fiscal year definition for any firm, as explained in footnote 10 in Section 1.

31. We drop observations for 1962 since the number of firms for which we could compute four-quarter growth rates is particularly small in that year. If we were to include 1962, the number of firms for which

we do not detrend the IQR in this case, but insert a linear trend in the regressions of the IQR on the recession indicator.

Finally, as Bloom et al. (2014) do in an effort to reduce the extent of changes in sample composition, we restrict the sample to firms for which at least 100 quarters of observations are available over the sample period. We refer to this as a sample of long-lived firms. Below, we discuss that we use a different definition of long-lived firms in cleaned samples "dc", the latter being the definition underlying our above results with the cross-sectional standard deviation.

We find that for both regular and DH sales growth, the IQR is higher during recessions and negatively correlated with quarterly and four-quarter GDP growth. All these results are significant at the 1% level. For DH sales growth, the IQR has a correlation of -0.30 with quarterly GDP growth and -0.50 with four-quarter GDP growth.

These results replicate the findings of Bloom et al. (2014) that the IQR of sales growth for Compustat firms is higher during recessions than at other times and has a correlation of -0.275 with GDP growth, both findings being significant at the 1% level.

The findings that the IQR is significantly higher during recessions than at other times and is strongly negatively correlated with GDP growth contrast with our findings from Section 5.1 that even with DH sales growth, our measure of firm-specific volatility does not rise significantly during recessions and has a fairly weak negative correlation with aggregate output growth. This difference in the measured degree of countercyclicality between the IQR and our measure could reflect the fact that we use a different measure, but it could also be due to differences in data processing.

To enhance comparability, we also report results when we detrend the IQR nonlinearly and/or clean the data as explained in Section 1. Another reason for doing so is that notwithstanding the restriction to long-lived firms, the quarterly number of available observations varies considerably in the sample "/". The number of firms rises from its minimum of 329 in 1963Q1 to its maximum of 1,928 in 1988Q2, and then gradually decreases to 1,105 in 2012Q3. This implies that the set of firms covered varies substantially over time, which leaves open the possibility that changes in sample composition affect measurement of the cyclical properties of the IQR.

In Table 4, for rows labeled "d", we continue to use the noncleaned sample of long-lived firms, but detrend the IQR by computing the percent difference from an HP trend with smoothing parameter 16,000. For rows marked "dc", we detrend the IQR and clean the data following the procedures in Section 1.

In the latter case, we only include firms for which 100 observations are available over the 140 quarter period 1978Q1–2012Q4 to which we restrict our cleaned samples. This implies a much stricter selection criterion than in the noncleaned sample,

we could compute regular and DH sales growth when restricting the sample to firms for which at least 100 quarters of observations are available over the period 1962Q2–2012Q4 is only 38 for 1962Q4 and lower for earlier quarters.

which we adopt so as to further reduce the extent of changes in sample composition. We use the same sample for generating the results with the cross-sectional standard deviation which we discussed at the beginning of this subsection.[32]

The results in rows “d” continue to indicate that the IQR is strongly countercyclical, with the negative relation being significant at the 1% level in all cases.

In rows “dc”, the IQR is still countercyclical. The correlations are smaller in absolute value, but still negative in all cases and mostly significant at the 5% level or better. For both regular and DH sales growth, the IQR is higher in recessions than at other times, and this difference is significant at the 1% level.

In Table 4, countercyclicality in the IQR for DH sales growth is consistently more pronounced than for regular sales growth. This plausibly results from the mathematical relation between the two growth rates, similar to our discussion at the end of Section 5.1. For the case “dc” with nonlinear detrending and cleaning, Table 4 also shows that the IQR in earnings growth rises during recessions and correlates negatively with GDP growth, all these results being significant at the 5% level.

Now focusing on DH sales growth for the row “dc”, we find that the IQR is typically 11.61% above trend in a recession, a difference of 14.28 percentage points with the IQR at other times that is significant at the 1% level. Moreover, the IQR has a correlation of −0.19 with quarterly GDP growth and −0.43 with four-quarter GDP growth, both of which are significantly different from zero.

Recall that our measure of firm-specific volatility in DH sales growth does not rise significantly during recessions. In addition, its correlations with quarterly and four-quarter GDP growth are only about half as large in absolute value as the correlations we just mentioned for the IQR. Therefore, even with comparable data cleaning, our measure of firm-specific volatility is less strongly countercyclical than the IQR for long-lived firms. Based on the argument that our measure more cleanly estimates firm-specific volatility, our interpretation is that evidence with the IQR for long-lived firms overstates the degree of countercyclicality in firm-specific volatility.

The difference between the IQR and our measure is particularly stark during the Great Recession. Before detrending in the cleaned sample of long-lived firms, the seasonally adjusted IQR for DH sales growth doubles from 15.31 in the quarter before the 2007Q4–2009Q2 recession to 30.65 at its peak in 2009Q1. This peak exceeds the IQR’s sample mean by 3.76 standard deviations. This is in sharp contrast with our finding from Section 3.1 that firm-specific volatility in DH sales growth increased moderately during the Great Recession, peaking at a level near its sample mean.

32. For rows labeled “dc”, the quarterly number of observations for regular and DH sales growth fluctuates in the comparatively narrow band of 473–536 between 1987Q1 and 2006Q4, which together with the requirement that firms be available for at least 100 of 140 observations indicates that the set of firms is fairly stable in that part of the sample period. The average quarterly number of observations is 471 over the entire sample period.

6. IS FIRM VOLATILITY A MAJOR DRIVER OF AGGREGATE FLUCTUATIONS?

In this section, we examine the dynamic relation between our measure of firm-specific volatility and the macroeconomy.

In our analysis, we pay particular attention to the implication from the model of Christiano, Motto, and Rostagno (2014) that an increase in firm-specific volatility causes a rise in the external finance premium and a slowdown in real activity. In this financial accelerator model, an increase in the volatility of firm-specific productivity shocks implies that a larger fraction of entrepreneurs default on their loan as their productivity falls below the threshold needed for repayment. Because of this, the external finance premium rises, which has a negative effect on investment and GDP.

Figure 4 shows the variables that we use. The top row shows detrended firm-specific volatility as discussed in Section 5.1. From left to right, the bottom row shows annualized quarterly growth in real GDP, in real investment,[33] and the detrended credit spread. The credit spread is a common empirical proxy for the external finance premium. We use the spread between Moody's seasoned Baa and Aaa corporate bond yields, detrended by computing the arithmetic difference from its HP trend with smoothing parameter 16,000.

Figure 5 shows impulse responses from a vector autoregression (VAR) with quarterly GDP growth, detrended economy-wide firm-specific earnings growth volatility and the detrended credit spread.

Throughout this section, we order real activity growth before firm-specific volatility. By assuming that firm-specific volatility does not affect real activity within the quarter, we assess the effect of shocks to firm-specific volatility that are orthogonal to real activity growth. We order the credit spread last, based on the intuition that a financial variable should react instantaneously to news about real variables. All reported results are for VAR lag order 4.[34]

A one-standard deviation shock to firm-specific earnings volatility, implying a rise in volatility of 3.26% above trend on impact, is followed by a rise in the credit spread peaking at 0.08 percentage points above trend three quarters after the shock, which is statistically significant at the 5% level albeit economically small. The same shock precedes a decline in annualized real GDP growth which reaches its trough at 0.44 percentage points two quarters after the shock. This decline is not statistically significant at the 5% level.

33. We compute real investment by deflating nominal private nonresidential fixed investment by the GDP deflator. Real GDP, GDP deflator, and nominal investment are from the Bureau of Economic Analysis after the 2013 comprehensive review of the National Income and Product Accounts.

34. Our main conclusions from the impulse responses, variance decompositions, and Granger causality tests reported in this section are robust to ordering firm-specific volatility before real activity growth, to using bivariate VARs that drop the credit spread, to using lag order eight, to using firm-specific volatility in manufacturing instead of across the whole economy, and to setting the smoothing parameter for detrending firm-specific volatility and the credit spread to the standard value of 1,600.

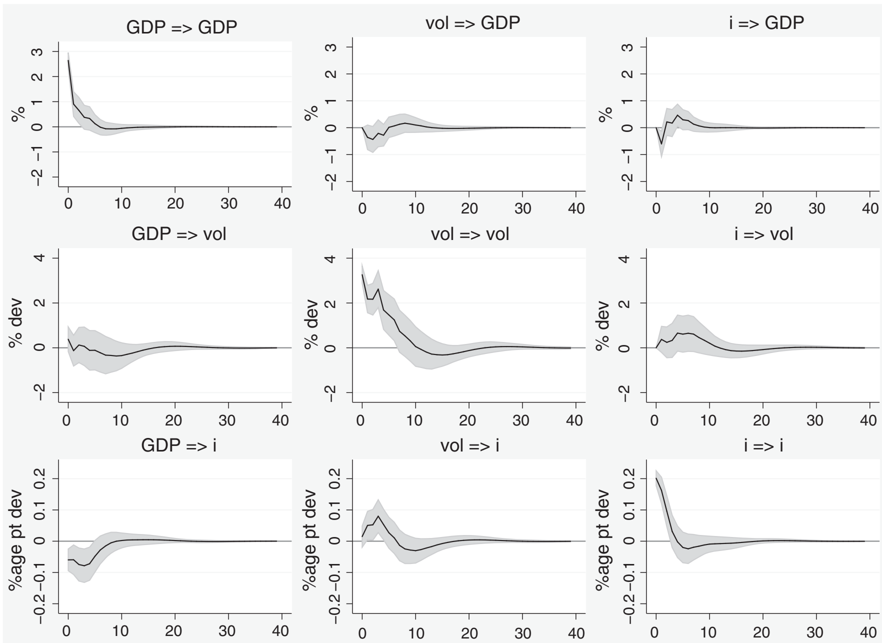

FIG. 5. Impulse Responses: GDP Growth, Firm-Specific Earnings Volatility, Credit Spread.

NOTE: This graph shows that an increase in firm-specific earnings volatility implies a small but statistically significant increase in the credit spread and a small, insignificant decline in real GDP growth. It shows impulse responses for a vector autoregression (VAR) with annualized quarterly real GDP growth, detrended economy-wide firm-specific earnings volatility, and the detrended credit spread, along with 95% confidence bands. Data are as plotted in Figure 4. In the titles for individual panels, "GDP" stands for real GDP growth, "vol" for firm-specific earnings volatility, and "i" for the credit spread. The panel title "vol => GDP" refers to the response of GDP growth to an impulse in firm-specific earnings volatility. Analogous meanings apply to the titles of the other panels. The horizontal axis shows quarters after the shock. Responses of GDP growth are in terms of annualized quarterly percentage changes, responses of firm-specific volatility in percent deviations from trend, and responses for the credit spread in percentage point deviations from trend. Results are for a VAR with lag order 4, and for a Cholesky decomposition that orders GDP growth first, firm-specific volatility second, and the credit spread third.

In a similar VAR with real investment growth instead of GDP growth, a one-standard deviation increase in earnings volatility is followed by a decline in investment growth that reaches its trough at 1.38 percentage points three quarters after the shock. Taken by themselves, these results are consistent with the hypothesis that an increase in firm-specific volatility leads to a widening in credit spreads and a slowdown in investment. However, the results indicate that the effect on credit spreads is very small, and the slowdown in investment does not translate into a substantial decline in GDP growth.

Results from similar VARs with regular and DH sales growth are at odds with the hypothesis that shocks to firm-specific volatility affect subsequent economic growth with a negative sign. If anything, a rise in firm-specific sales volatility is followed by increasing real activity growth.

Focusing on earnings volatility, we find that variance decompositions for the VAR with the same variables as that for which Figure 5 graphs impulse responses imply that at a long horizon (100 quarters), firm-specific volatility explains 15.71% of the forecast error variance of the credit spread and 5.35% of that of real GDP growth. In a comparable VAR with investment growth, firm-specific volatility explains 8.21% of the variance of the credit spread and 7.88% of the variance of investment growth.

Furthermore, we find that firm-specific earnings growth volatility does not Granger cause real GDP growth or real investment growth. In the VAR for which Figure 5 graphs impulse responses, the F-statistic for the joint significance of the volatility terms in the GDP growth regression is 0.78, with a p-value of 0.54. The analogous test with investment growth has an F-statistic of 1.22 and a p-value of 0.31.

In bivariate VARs, firm-specific earnings volatility similarly does not Granger cause GDP growth or investment growth.

Therefore, our findings suggest that to the extent that firm-specific volatility affects the economy with a negative sign, idiosyncratic volatility explains a small fraction of macroeconomic fluctuations, and does not significantly add to explaining in-sample variation in real activity growth beyond the information contained in lagged growth rates.

In addition to the effect of unanticipated shocks to firm-specific volatility on real activity, the theory of Christiano, Motto, and Rostagno (2014) features an effect of anticipated changes in volatility. This raises the possibility that some changes in firm-specific volatility shine through in real activity before the change in volatility actually happens. Any such response of real activity to future changes in firm-specific volatility would not be picked up by the dynamic responses to a volatility impulse which we discussed above.

In a trivariate VAR with GDP growth, firm-specific volatility in DH sales growth and the credit spread, we find that a one-standard deviation rise in GDP growth, amounting to an increase by 2.62 percentage points, is followed by a statistically significant decline in firm-specific volatility that reaches its trough at 1.33% below trend one quarter after the shock. In similar VARs with regular sales and earnings growth, an impulse increase in GDP growth predates a much smaller and insignificant decline in volatility, if anything.

Focusing on the result with DH sales growth, it is not clear whether the finding that an impulse increase in GDP growth predates declining firm-specific volatility reflects an economic response of GDP to subsequent changes in firm-specific volatility. In our view, a natural interpretation is that firm-specific volatility is endogenous, in the sense that booms make firms somewhat less volatile.

To sum up, our evidence suggests that firm-specific volatility is not a major driver of macroeconomic fluctuations. Our assessment is that the moderate degree of countercyclicality which we found with DH sales growth in Section 5.1 reflects endogeneity in firm-specific volatility rather than an effect of volatility on the economy.

7. CONCLUSION

In this paper, we find that firm-specific sales and earnings volatility increase only moderately during recessions and have a weak contemporaneous association with GDP growth. Our interpretation is that the negative association between firm-specific volatility and the business cycle is less pronounced than it appears from earlier evidence with the interquartile range.

Our evidence on the dynamic relation between firm-specific volatility and real activity suggests that firm-specific volatility is not an important driver of macroeconomic fluctuations. However, our results allow for the possibility that firm-specific volatility is endogenous in the sense that economic downturns make firms somewhat more volatile.

Finally, we find that the case for a trend increase in idiosyncratic volatility of publicly traded firms entirely disappears once we control for changes in sample composition regarding the typical level of volatility of a firm. A typical publicly traded firm is more stable toward the end of our sample than at any other point of time since 1978. This enhanced stability explains our finding that while firm-specific volatility increased moderately during the 2007–2009 recession, volatility never substantially exceeded its sample mean during that recession and remained below the volatility levels of the late 1990s.

Our findings have the following implications for future research.

First, our paper contributes to the measurement of firm-specific volatility. Further improvements are possible, such as controlling for a larger set of factors that could account for predictable changes in firm-level growth.

Second, finding out to which extent our findings with sales and earnings speak for the cyclical properties of firm-specific volatility in underlying productivity growth requires further research.

Third, while we find that firm-specific volatility in sales and earnings growth increases moderately around the time of recessions, Campbell et al. (2001) find that the firm-level variance in stock returns roughly doubles in recessions.[35] This suggests that firm-specific volatility in stock returns rises more sharply in recessions than idiosyncratic volatility in economic variables. If that is indeed the case, one possible explanation is that the countercyclicality of idiosyncratic stock return volatility reflects countercyclical volatility of risk premia as well as countercyclical volatility of economic fundamentals. This hypothesis requires further research.

Fourth, we find that recessions mark turning points between periods with increasing and decreasing firm-specific volatility. Volatility decreases from shortly after the 1981–1982 recession until the 1990–1991 recession, then increases until the 2001 recession, and then decreases until the 2007–2009 recession. While the literature to date has focused on whether volatility is higher during recessions, future research may seek to explain these patterns in between recessions.

35. See Campbell et al. (2001, p. 31).

One possible explanation is that firms' attitude to risk may gradually change in response to 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, possibly explaining the decrease in firm-specific volatility until the 1990–1991 recession. 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-specific volatility increasing as a result.

APPENDIX A

In this appendix, we show that a variant of the framework in equations (4)–(6) is equivalent to computing cross-sectional standard deviations by sector. Notation is as in those equations.

First, run the following regression by sector:

$$\gamma_{it} = c + b_t + \varepsilon_{it}. \tag{A1}$$

This equation includes a constant and time effects. For identification, set the time effect for the first quarter to zero, such that the constant indicates the cross-sectional average of growth rates in the first quarter. In that case, for any other quarter t, $\widehat{c} + \widehat{b_t} = \overline{\gamma}_t$, the cross-sectional average at time t of the firm-level growth rates γ_{it} in the sector. Therefore, the residual $\widehat{\varepsilon}_{it} = \gamma_{it} - \overline{\gamma}_t$.

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

$$\left(\widehat{\sigma}_{\varepsilon,it}\right)^2 = (\widehat{\varepsilon}_{it})^2 \tag{A2}$$

and run a sector-level regression of that estimate of the variance on time effects:

$$\left(\widehat{\sigma}_{\varepsilon,it}\right)^2 = k + \beta_t + \nu_{it}. \tag{A3}$$

In equation (A3), $\widehat{k} + \widehat{\beta_t}$ is the cross-sectional average of the squared residuals from equation (A1). That is to say, $\widehat{k} + \widehat{\beta_t} = (1/N_{st}) \sum_{i=1}^{N_{st}} (\gamma_{it} - \overline{\gamma}_t)^2$, with N_{st} the number of firms in sector s in period t. This implies:

$$\sqrt{\frac{N_{st}}{N_{st} - 1}(\widehat{k} + \widehat{\beta_t})} = \sqrt{\frac{1}{N_{st} - 1} \sum_{i=1}^{N_{st}} (\gamma_{it} - \overline{\gamma}_t)^2}. \tag{A4}$$

Therefore, using equations (A1)–(A4) to obtain $\sqrt{[N_{st}/(N_{st} - 1)](\widehat{k} + \widehat{\beta_t})}$ is equivalent to computing the cross-sectional standard deviation for any period t by sector.

APPENDIX B

In this appendix, we derive the function that relates DH sales growth to regular sales growth. We discuss that relative to regular growth, the DH formula dampens positive firm-level growth and amplifies negative growth.

Rearranging the formula for regular growth g_{it}^1, equation (1) in the main text, we obtain:

$$\frac{S_{it}}{S_{i,t-4}} = \frac{g_{it}^1}{100} + 1, \tag{B1}$$

where S_{it} and $S_{i,t-4}$ are the level of sales for firm i in t and $t-4$, respectively.

Rearranging the formula for DH growth g_{it}^2, equation (2) in the main text, we obtain:

$$g_{it}^2 = \frac{(S_{it}/S_{i,t-4}) - 1}{(S_{it}/S_{i,t-4}) + 1} * 200. \tag{B2}$$

Substituting the expression for $S_{it}/S_{i,t-4}$ from equation (B1) into (B2) and rearranging yields:

$$g_{it}^2 = f\left(g_{it}^1\right) = \frac{200 g_{it}^1}{200 + g_{it}^1}, \tag{B3}$$

which implies $f(0) = 0$, $f(-100) = -200$, and $\lim_{g_{it}^1 \to +\infty} f(g_{it}^1) = 200$. The first derivative is:

$$f'\left(g_{it}^1\right) = \frac{40{,}000}{\left(200 + g_{it}^1\right)^2}, \tag{B4}$$

which implies that $f'(0) = 1$ and $f'(g_{it}^1) > 0$ at all points. Since $f(0) = 0$, the latter implies that $sgn(g_{it}^2) = sgn(g_{it}^1)$. The second derivative is:

$$f''(g_{it}^1) = -\frac{80{,}000\, g_{it}^1 + 16{,}000{,}000}{\left(200 + g_{it}^1\right)^4}. \tag{B5}$$

Since $g_{it}^1 \in [-100, +\infty)$ for non-negative sales, $f''(g_{it}^1) < 0$ at all points on the support.

Therefore, the DH growth rate is a sign-preserving, monotonically increasing and strictly concave function of regular growth with slope one at the origin. By concavity, the slope exceeds one for negative firm-level growth, such that the DH formula amplifies negative growth. Analogously, the slope is below one for positive growth, such that the DH formula dampens positive growth.

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