Cyclical Changes in Firm Volatility*

Emmanuel De Veirman and Andrew Levin†

May 28, 2010

Abstract

We develop a new technique for estimating earnings and employment volatility at the firm level, and apply it to US and Japanese firms. Our measure of firm volatility differs from existing measures in that its fluctuations are interpretable at business cycle frequencies. Volatility tends to increase if an adverse event has not materialized in the recent past, and gradually declines in the aftermath of an adverse aggregate event. We interpret this pattern as reflecting time-variation in risk awareness.

JEL codes: C33, D21, E23, E24

Keywords: Firm-Level Volatility.

---

*We thank Laurence Ball, Andrew Coleman, Ippei Fujiwara, Dean Hyslop, Alejandro Justiniano, Özer Karagedikli, Ken Kuttner, David Lucca, Robert Moffitt, Fumio Ohtake, Ayako Suzuki, Alex Wolman, and Raf Wouters for feedback and assistance. We also thank seminar participants at the National Bank of Belgium, the Board of Governors and the Reserve Bank of New Zealand for comments. Any errors and omissions are the responsibility of the authors. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Reserve Bank of New Zealand or the Federal Reserve System.

†Emmanuel De Veirman (corresponding author), Reserve Bank of New Zealand, 2 The Terrace, Wellington, New Zealand. E-mail: Emmanuel.Deveirman@rbnz.govt.nz. Andrew T. Levin, Board of Governors of the Federal Reserve System, 20th Street and Constitution Avenue NW, Washington DC 20551.
1 Introduction

The variance of shocks is often modeled as time-invariant in structural models of the business cycle. In this paper, we develop an empirical procedure to estimate time-variation in output dispersion induced by firm-specific shocks. We apply this procedure to US and Japanese firms. In both economies, we detect substantial variation in firm volatility at business cycle frequencies.

Our paper contributes to a relatively recent empirical literature that has estimated time-variation in the volatility of firm-level sales, earnings and employment growth in the United States. The existing literature on this topic focuses on trend changes in firm volatility over relatively long time horizons, and compares findings at the firm level to a well-documented longer-term decline in aggregate volatility.\(^1\) Comin and Philippon (2005) and Comin and Mulani (2006) document that, in a trend sense, publicly traded US firms have become more volatile than they were in the mid-1950s. Davis, Haltiwanger, Jarmin, and Miranda (2006) confirm this finding, and also find that combining listed and privately held firms, a typical US firm has experienced a trend decline in volatility.

Unlike these papers, our aim is not to gauge how trends in firm volatility compare to trends in aggregate volatility. In fact, our US data sample spans a period of relative aggregate stability. Our interest is to uncover changes in firm volatility at a higher frequency, which -as we argue in a minute- plausibly have independent macroeconomic implications. We develop a new methodology to do precisely that.

To our knowledge, this is the first paper that presents evidence on instantaneous changes in

firm-level sales and employment volatility for US firms. For Japan, we are the first to estimate changes in firm-level volatility of non-financial variables per se.\textsuperscript{2}

The macroeconomic relevance of having a measure of firm volatility with interpretable short-term changes can be understood in a number of ways.

First, episodes in which the volatility of firm-specific shocks is large may systematically tend to anticipate a macroeconomic downturn. One economic rationale for this lies in Christiano, Motto, and Rostagno’s (2009) model with financial frictions in which the volatility of firm-specific productivity shocks varies stochastically. In their model, an increase in the dispersion of the distribution of firm-specific shocks implies an increase in borrower risk, in the sense that a larger fraction of borrowers will default. News about an upcoming adverse ‘risk shock’ implies an increase in the external finance premium and a decrease in lending. In turn, a rise in the cost of external finance implies declines in investment, consumption, and aggregate output.

Another reason for rises in firm-level volatility to anticipate recessions is incorporated in Bloom’s (2009) model of high-frequency uncertainty shocks and irreversibility of investment and hiring decisions. In this model, large and short-lived increases in uncertainty cause firms to postpone adjusting capital and labor stocks. This implies a sharp short-run decline and ensuing rebound and overshoot in aggregate output.\textsuperscript{3}

A second way in which firm volatility matters macroeconomically is its relationship to firms’ pricing decisions and the degree of non-neutrality associated with macroeconomic shocks. The current generation of state-dependent pricing models typically includes firm-specific productivity

\textsuperscript{2}There is a more elaborate literature investigating time-variation in the firm-specific and aggregate components of the volatility of stock market returns. For the United States, see Campbell, Lettau, Malkiel and Xu (2001), Malkiel and Xu (2003), Fama and French (2004), Fink, Fink, Grullon, and Weston (2005), and Brown and Kapadia (2007). For Japan, see Hamao, Mei, and Xu (2007).

\textsuperscript{3}See also Bloom, Floetotto, and Jaimovich (2009).
This follows from the insight that firm-specific shocks dominate firms’ pricing decisions and have a large effect on repricing rates, while aggregate factors such as inflation and monetary policy shocks have comparatively little impact on repricing rates. Therefore, periods of high volatility of firm-specific shocks would tend to be associated with high frequencies of price adjustment. Our intuition is that firms would use these re-optimizations to also incorporate the effect of macroeconomic shocks. Therefore, monetary policy and other macro shocks would be more quickly priced in at times of high firm-specific volatility, and would have smaller real effects.

Our results indicate substantial short-run variation in firm-level volatility. There is something to the claim that periods of high volatility tend to anticipate macroeconomic downturns, as the financial accelerator and irreversibility models would imply. More specifically, we find that firm volatility has tended to be high or to increase in periods leading up to adverse aggregate events, and has tended to decline in their aftermath. Our intuition is that this pattern suggests that firms and their contractual counterparties have some degree of influence over the distribution of firm-specific risks and firm-specific degree of exposure to aggregate risks. In particular, we conjecture that a decrease in risk awareness during benign periods may lead firms to take more risky decisions, while an adverse event that hits firms across the board implies an increase in perceived riskiness and therefore a more cautious approach in terms of financing, hiring, and product development decisions, implying a gradual decrease in realized conditional volatility.

Our paper is structured as follows. Section 2 discusses data and measurement issues. Section 3 lays out the estimation model. Section 4 discusses our baseline results. Section 5 summarizes results for separate sectors and firm size quartiles, and documents the robustness of our results to

\footnote{See Dotsey, King, and Wolman (2009), Golosov and Lucas (2007), Gertler and Leahy (2008), as well as Klenow and Willis (2006), Costain and Nakov (2008), Midrigan (2009), Burstein and Hellwig (2007), and Nakamura and Steinsson (2008).}
using an alternative sample of firms. Section 6 interprets and concludes.

2 Data and Measurement

2.1 Data and Sample Selection

We estimate firm-level volatility in the growth rates of net sales, Earnings Before Interest and Taxes (EBIT), and the number of employees. The results reported in this paper are based on nominal sales and earnings data. However, our results are virtually unchanged when we deflate sales and EBIT by the aggregate Producer Price Index (PPI).

For both the United States and Japan, we use firm-level data from the Thomson Worldscope database. The Worldscope data are available at an annual frequency. For each country, we use growth rates for the period 1986-2005.

For the United States, we work with a sample of 15,425 firms that are incorporated in the US and are listed on at least one of the US stock exchanges. This sample excludes entities in public administration. It also excludes firms which trade on the US stock markets only through American Depositary Receipts, as well as other firms that indicate a physical address outside the US.

For our sample of Japanese firms, we downloaded data for all 4,507 Japanese firms in Worldscope. All of these are incorporated in Japan and have their primary listing on one of the Japanese stock exchanges.

All firms in our dataset are publicly traded. We share this feature with Comin and Philippon.

---

5 Net sales equals gross sales, i.e. the amount of actual billings to customers for regular sales, minus cash discounts, trade discounts, and returned sales and allowances for which credit is given to the customer.

EBIT is computed as a firm’s sales and other income minus its operating expenses, which include fixed costs, marginal costs, and depreciation, yet do not include interest and tax payments. Thus, EBIT reflects the profitability of the firm’s operations, abstracting from tax expenditure, as well as from interest expenses and interest income.

The number of employees for any company includes both full-time and part-time employees, but excludes seasonal employees and emergency employees.

6 Data for a restricted number of firms are available for the first half of the 1980s.

7 Beyond 17 entities in the SIC division public administration, the sample of 15,425 US firms excludes 1,302 firms only listed through ADRs and 53 additional firms that indicate an address outside of the US. Beyond that, we exclude 269 firms with empty primary SIC code and 199 firms that the SIC lists as nonclassifiable.
(2005) and Comin and Mulani (2006). However, Davis, Haltiwanger, Jarmin and Miranda’s (2006) findings suggest that over our sample period, trend changes in US firm volatility are different for privately held than for publicly traded firms. We expect that, if we were to include privately held firms as well, this would imply a moderate trend decline in volatility over our sample. But without further evidence, our best estimate is that the cyclical swings in volatility would apply to privately held firms as well.

Davis e.a. (2006) explain much of the volatility trends by changes in the composition of firms. In particular, they attribute most of the increase in volatility of listed firms to the fact that more recently listed firms appear to be intrinsically more volatile, presumably because the selection criteria for being listed on the stock market have changed over time. In addition to this issue, we have to deal with the fact that Worldscope has expanded its coverage of listed firms over time. In so doing, Worldscope has implicitly relaxed the criteria for inclusion in the database. In particular, smaller firms tend to have been included at a later data than larger firms. This change in sample composition matters in particular because of the stylized fact that smaller firms tend to be more volatile.

Once a firm is included in the sample, it is bound to stay, as long as it continues to exist as a listed company. Therefore, when a new firm appears in the database, this does not necessarily reflect a new listing, while disappearing firms more likely reflect delistings or firm deaths.

As Figure U1 illustrates for the United States, and Figure J1 does for Japan, this is reflected in a trend decline in net sales, operational profit and the number of employees for most parts of the distribution, a decline which we do not take to be representative for the overall population of

---

8The number of US firms for which data on net sales are available in Worldscope increases from 2573 in 1986 to 7698 in 2005. Coverage of listed firms expanded in particular during the 1990s and appears to be complete after that. The number of Japanese firms for which data on net sales are available increases from 1073 in 1986 to 3921 in 2005.
firms. Note that in the US, there is a reversal in this trend from about 2000. This is partly due to delisting in the aftermath of the 2000 stock market crash. In the two Figures we just introduced, large diamonds indicate the median in a given year, small diamonds indicate the 25th and 75th percentiles, and the dashed line indicates the mean. Note that the mean substantially exceeds the 75th percentile, suggesting skewness in the distribution of firms.

We control for changes in sample composition in two ways.

First, our baseline regressions only include firms for which data on all three growth rates (sales, earnings and employment) have been continuously available for every of the twenty years in the sample. This yields a balanced panel of 588 US firms, and one of 577 Japanese firms. This effectively holds the composition of firms stable over time, with a stable sectoral composition and a relatively stable size distribution (although the total sales from included firms become gradually larger as a fraction of GDP).

Second, we find that our conclusions are robust to subdividing these data in firm size quartiles. In that case, all observations in a subsample are within well-defined bands as far as firm size is concerned, which is a way of holding size relatively constant.

A disadvantage of the balanced panel is that it is bound to contain a disproportionate fraction of large firms, and firms that grow in a comparatively stable fashion. Figure U3 indicates a stable upward trend in sales, profits and the number of employees in the balanced panel of US firms, with the exception of slowdowns in the recessions of the early 1990s and 2001. As for the sample of continuously available Japanese firms, Figure J3 does not indicate a generalized trend decline in firm size, although median profitability declined through the 1990s. In both countries, the combined sales of the continuously available firms tend to increase at a faster rate than aggregate GDP does, suggesting that their composite value-added accounted for an increasingly large share
of overall production. The fact that firm size increases somewhat over the sample may tend to bias our results towards finding a decline in volatility.

Therefore, we examine robustness by estimating volatility for the full Worldscope samples, of 15,425 firms in the US case and of 4,507 firms in the Japanese case. In that exercise, we control for firm fixed effects, implying that our estimate of average volatility is less affected by the gradual extension of the sample to firms that are intrinsically more volatile. In this case, we include the available observations for companies which became inactive before the last year of the sample, in an effort to avoid survivorship bias. As we will discuss, the volatility patterns with the full Worldscope sample are similar to those obtained from the balanced panel of continuously available firms, with the exception of the fact that in the US, the level of volatility is substantially larger in the former sample than in the latter. Our main conclusions regarding cyclical swings in firm volatility apply in these two very different samples, which suggests that they are not purely driven by changes in composition.

2.2 Measurement

We compute annual growth rates in net sales and employment. For Earnings Before Interest and Taxes (EBIT), we cannot compute the growth rate for any year \(t\) in the regular fashion, since doing so would yield meaningless results when EBIT is negative in \(t\) and/or \(t-1\). Therefore, we compute growth in operational profit based on the change in EBIT divided by lagged net sales:

\[
\gamma_{it} = \frac{EBIT_{it} - EBIT_{i,t-1}}{SALES_{i,t-1}} \times 100
\]

\[ \text{We computed sales growth after dropping observations for which net sales is strictly negative (23 observations in the US, and three observations in Japan). The reported results are based on growth rates computed in the regular fashion. For instance, the sales growth rate of firm } i \text{ in year } t \text{ is } \gamma_{it} = \frac{SALES_{it} - SALES_{i,t-1}}{SALES_{i,t-1}} \times 100. \text{ However, for the US we examined robustness with respect to the measure that Davis e.a. (2006) use: } \gamma_{it} = \frac{SALES_{it} - SALES_{i,t-1}}{SALES_{i,t} + SALES_{i,t-1}} \times 100. \text{ The results (not reported here) are very similar to our baseline case.} \]
We do not account for firm entry or exit, in the sense that we require two consecutive observations on sales, employment, or EBIT in order to compute the growth rates.

We windsorize the data in order to reduce the impact of outliers on our results. For every growth rate, we determine the 2.5th and 97.5th percentiles of all observations in the full Worldscope samples. We replace any (negative) growth rate which falls below the 2.5th percentile by the value of the growth rate at the 2.5th percentile. Similarly, we replace any (positive) growth rate exceeding the 97.5th percentile by the value of the growth rate at the 97.5th percentile. When restricting the sample to continuously available firms, we use the data as windsorized based on the percentiles applicable to the unrestricted sample of firms. That is, we effectively windsorize even less than five percent of the restricted sample’s observations.

Figures U2 and U4 graph the distribution of sales, EBIT, and employment growth for the full Worldscope sample of US firms and for the balanced panel of 588 firms, respectively. Looking at the balanced panel, the firm-level data accurately indicate slowdowns at the time of the recessions of the early 1990s and of the early 2000s. The same feature is present in the unrestricted sample. Dispersion in growth rates across firms appears to be larger in the unbalanced panel, a finding that we confirm more formally below.

Figures J2 and J4 graph the distribution of sales, EBIT, and employment growth for the full Worldscope sample of Japanese firms and the balanced panel of 577 firms, respectively. Median sales growth of sampled firms plausibly corresponds to aggregate Japanese developments: it reflects the high-growth bubble of the late 1980s, the fact that GDP growth was subdued but still mostly positive in the first half of the 1990s, and the fact that the economy experienced a severe downturn in the second half of the 1990s, before recovering around 2003.

In Figure J3, note the large upward jump in employment in 2000. This reflects the fact
that for business years ending on March 31, 2000 or later, Japanese companies have implemented substantial changes in accounting standards. In particular, the new standards have broadened the definition of subsidiaries which parent companies are required to include in their consolidated accounts. While the change in accounting standards may explain the temporary increase in the levels of sales and profit in 2000, the change in rules appears to have had most impact on reported employment figures. This makes some sense: before the change in accounting standards, parent companies had often assigned their excess employment (and excess debt) to affiliate companies which did not need to be included in the consolidated accounts.

We deal with this issue in two ways. First, we omit all Japanese firms’ growth observations for which consolidation practices differ from that in the previous year. Second, we omit Japanese employment growth data for 2000 and 2001. Neither Figure J2 nor Figure J4 graph employment growth for those years, but one can readily infer from Figure 3 that the growth rates corresponding to the levels jump in employment levels in 2000 are extremely high. The issue appears less severe in the case of sales and earnings growth, and we do not omit observations for these variables. In any case, our technique is such that estimated volatility for other years is invariant to the inclusion of observations for 2000 and 2001.

3 Estimation Model

This section describes the procedure which we use to estimate firm volatility.

Our approach differs from the methodology used thus far in the literature. Comin and Philippon (2005), Comin and Mulani (2006) and Davis e.a. (2006) all measure firm-level volatility based on rolling ten-year standard deviations of firm-level growth rates.\textsuperscript{10} In particular, they measure firm

\textsuperscript{10}Davis e.a. (2006) also consider a modified rolling standard deviation which accounts for firms for which growth rates are available for less than ten years.
volatility for every firm $i$ in year $t$ as:

$$
\sigma_{it}^r = \sqrt{\frac{1}{10} \sum_{\tau=-4}^{\tau=5} (\gamma_{i,t+\tau} - \bar{\gamma}_{it})^2}
$$

(2)

Where $\bar{\gamma}_{it}$ is the firm’s average growth rate between year $t - 4$ and $t + 5$. Depending on the paper, this measure is then aggregated by taking medians or averages (size-weighted or not) across firms. In this way, one derives ten-year averages of volatility. For instance, measured volatility for 2000 depends on fluctuations in growth rates between 1996 and 2005. It therefore does not estimate volatility for the year 2000 specifically, but it estimates average volatility during a ten-year window around it. This measure is particularly suitable for evaluating trend changes in firm volatility. For instance, to compare firm volatility today to firm volatility three decades ago, it is preferable not to compare estimates of firm volatility for two individual years, since these individual years may not be representative for their particular period.

However, since the aggregated version of equation (2) does not imply an instantaneous estimate for volatility in any particular year, it is not designed to accurately capture year-on-year changes in volatility. To see this point, note that the overlapping nature of the rolling standard deviations implies that annual changes in volatility are smoothed out. As another way to see this point, note that any change in a firm’s rolling standard deviation from $t - 1$ to $t$ will reflect both the growth rate in $t + 5$ which enters $\sigma_{it}^r$ but not $\sigma_{i,t-1}^r$, and the growth rate in $t - 5$ which does not appear in $\sigma_{it}^r$ but does so in $\sigma_{i,t-1}^r$. Changes in measured volatility are thereby no pure measure of changes in actual volatility in any year, whether $t$, $t - 5$, or $t + 5$.

Our measure differs from the above methodology in that it yields an estimate of instantaneous firm volatility for every year.

A second difference between the predominant methodology and ours is that rolling standard de-
viations capture the overall variation in firm-level earnings growth, without distinguishing between variation induced by firm-specific factors and volatility due to aggregate or sector-wide developments. In this paper, we separately estimate the firm-specific component of firm-level volatility, which is novel for earnings and employment volatility,\textsuperscript{11} but is inspired by the literature on US stock market volatility.\textsuperscript{12}

Our model consists of two equations with a panel data structure. The first-stage regression is as follows:

\[
\gamma_{it} = c + \sum_{j=2}^{J} a_j \eta_j + \sum_{\tau=1987}^{2005} b_{\tau} \lambda_{\tau} + \sum_{q=2}^{Q} \sum_{\tau=1987}^{2005} e_{q\tau} \vartheta_{q} \lambda_{\tau} + \sum_{s=2}^{S} \sum_{\tau=1987}^{2005} d_{s\tau} \varphi_{s} \lambda_{\tau} + \varepsilon_{it} \quad (3)
\]

Variables are denoted by Greek symbols while Arabic letters correspond to coefficients. Throughout, we use growth rate data for the period 1986-2005. The left-hand side variable \(\gamma_{it}\) represents net sales growth, EBIT growth, or employment growth between year \(t-1\) and \(t\) for firm \(i\). We write the constant as \(c\). The coefficients \(a_j\) on the firm dummies \(\eta_j\) capture firm \(j\)’s average growth rate over the sample (relative to the growth rate of firm 1).

The effects of (unobserved) aggregate factors on firm growth are captured by the coefficients \(b_{\tau}\), \(e_{q\tau}\) and \(d_{s\tau}\) on the terms involving time dummies \(\lambda_{\tau}\). By virtue of dummy interaction terms involving size quartile dummies \(\vartheta_{q}\) and sector dummies \(\varphi_{s}\), respectively, we allow aggregate factors to have a different impact on firm growth depending on a firm’s size and the sector in which it operates.\textsuperscript{13}

\textsuperscript{11}Castro, Clementi, and Lee (2009) also filter aggregate effects from total firm-level volatility. However, they focus on differences in volatility across sectors, while we focus on changes in volatility over time.

\textsuperscript{12}Campbell, Lettau, Malkiel, and Xu (2001) decompose stock market volatility into a market-wide, sector-specific, and idiosyncratic component. Recent contributions to the literature on firm-level stock market volatility include Fama and French (2004) and Fink, Fink, Grullon, and Weston (2005).

\textsuperscript{13}We do not weigh observations by firm size. Since our sample does not include privately held firms, we prefer to weigh comparatively small listed firms equally to larger firms. In any case, our main conclusions are robust across
To see the intuitive appeal of the dummy interactions, note that aggregate factors likely have systematically different effects on firm growth depending on the sector in which a firm operates. For instance, growth rates of service providers may be particularly vulnerable to aggregate shocks. This could be true because labor constitutes a particularly large share of service firms’ input costs, and if wages are less flexible than the prices of other production factors. For example, firms would find it hard to reduce the real wage in response to an adverse oil shock, and their sales and profitability may therefore be harder hit.

Aggregate factors also likely have a different impact on firm growth depending on the firm’s size. It is a stylized fact that smaller firms tend to be more volatile. This may in part reflect the possibility that they face larger firm-specific shocks, for instance because shocks at the establishment level are averaged over fewer establishments. But it is plausible that some of the high volatility in small firms is induced by a higher level of vulnerability to aggregate conditions.

Equation (3) reflects the fact that, to avoid perfect collinearity, we drop one dummy each for the year, sector, and size effects, and any interaction terms in which these dummies appear.

In the baseline, we focus on the balanced panels of firms, such that $J = 588$ for the United States and $J = 577$ for Japanese firms. The corresponding numbers for the unrestricted samples are 15 425 and 4507, respectively.

To construct the firm size dummies $\vartheta_q$, we divide observations for the relevant sample into quartiles according to their sales-to-GDP ratio. This implies that $Q = 4$.

In this paper, we report results when classifying data into three broad sectors, that is to say, $S = 3$. Results do not materially change when we consider more disaggregate sectors. We choose different firm size quartiles. (See the robustness section.) This suggests that assigning more weight to larger firms would not alter our main conclusions.

14Using the number of employees as the criterion to create firm size quartiles makes a barely noticeable difference for any of the results reported in this paper.
three sectors since it ensures that we have sufficient firms in every sector for every year.

For the United States, we used data on each firm’s primary SIC code to classify firms into those active in manufacturing (the SIC division manufacturing), services (which groups three SIC divisions: services, wholesale trade, and retail trade), and other sectors (which combine the five remaining private-sector SIC divisions: agriculture, forestry, fishing; mining; construction; transportation, communications, electric, gas, sanitary service; and finance, insurance, real estate).

In assigning Japanese firms to sectors, we made an effort to ensure comparability of our sector classification to the one we use for the United States. In Worldscope, Japanese firms are classified according to the Global Industry Classification Standard (GICS). There are ten two-digit GICS sectors. In practice, many of these sectors comprise a heterogeneous set of firms. For instance, the sector ‘industrials’ contains not only manufacturers of products such as defense equipment, power-generating equipment and heavy trucks, but also the distributors of these products. That same sector also contains businesses providing commercial services such as printing or human resources services. The sector also includes transportation firms such as airlines and railroad companies.

To make our results for Japanese firms more intelligible, we use data on eight-digit GICS sub-industries to assign all firms to three broad sectors corresponding to those for the US: manufacturing, services (which we is again broadly defined, to include wholesalers and retail traders), and other sectors (including education, utilities, health, financial services, transport, agriculture, and mining).

The first-stage regression, equation (3), is related to Kim and Nelson (1999) and McConnell and Perez-Quiros (2000), who model instantaneous aggregate volatility as the variance and standard deviation, respectively, of the error term of an autoregressive process in real GDP growth.

15The ten GICS sectors are: energy; materials; industrials; consumer discretionary; consumer staples; health care; financials; information technology; utilities; and telecom.
Given that we control for aggregate factors $\lambda_{\tau}$ in equation (3), the regression residual $\varepsilon_{it}$ captures the firm-specific component of the deviation of firm growth from its time-varying mean. The residual $\varepsilon_{it}$ is assumed to be normally distributed with mean zero and variance $\sigma_{\varepsilon, it}^2$. In analogy with McConnell and Perez-Quiros (2000), we proxy the standard deviation $\sigma_{\varepsilon, it}$ by $\sqrt{\sum |\hat{\varepsilon}_{it}|}$, a term proportional to the absolute value of the first-stage residual. If $\varepsilon_{it}$ is normally distributed, this is an unbiased estimator of the standard deviation of $\varepsilon_{it}$.

At the level of the individual firm, a high value for $\sigma_{\varepsilon, it}$ implies high volatility in that firm’s growth rate in year $t$. The volatility is firm-specific in the following sense. First, it tends to be induced by shocks specific to firm $i$. Second, it tends to mean that firm $i$ was more exposed to aggregate shocks than a typical firm in its sector and firm size quartile, that is to say, it responds more to aggregate factors than the factor loadings on $\lambda_{\tau}$ and its interaction terms imply.

When firm-specific volatility is high for many firms, this induces a high level of dispersion in the distribution of growth rates. When many firms in a particular sector/firm size category have a high value for $\sigma_{\varepsilon, it}$, then this also means that they tend to deviate substantially from the sector- and firm size-specific mean growth rate. Our measure therefore captures both dispersion and volatility in firm growth rates in a single procedure. Computing separate measures, Davis e.a. (2006) find that firm volatility and cross-section dispersion behave similarly.

Our second-stage regression aggregates the estimated values for $\sigma_{\varepsilon, it}$. In the balanced panels, we regress:

$$\hat{\sigma}_{\varepsilon, it} = k + \sum_{\tau=1987}^{2005} f_{\tau} \delta_{\tau} + \nu_{it}$$

Equation (4) entails regressing firm-specific volatility on a constant and time effects. The coefficients on the time dummies $\delta_{\tau}$ capture the cross-sectional average of idiosyncratic firm-level
volatility in any year \( \tau \). The error term \( \nu_{it} \) is in principle independently and identically distributed with mean zero and variance \( \sigma^2 \nu \).

Plotting the coefficients on the second-stage time dummies \( \delta_{\tau} \) and their standard errors over time yields a visualization of the time-path of average firm-level volatility, controlling for firm fixed effects. In particular, the constant \( k \) captures average idiosyncratic volatility in 1986, while we compute average firm-level volatility for any other year \( \tau \) as \( k + f_{\tau} \).

An alternative procedure would have been to literally compute the average of firm-specific volatility for every year. The advantage of regression (4) is that it conveniently delivers standard errors around the volatility estimates.\(^{16}\)

In the unbalanced panels, our second-stage regression is as follows:

\[
\hat{\sigma}_{\varepsilon, it} = k + \sum_{\tau=1987}^{2005} f_{\tau} \delta_{\tau} + \sum_{j=2}^{J} g_j \zeta_j + \nu_{it}
\]  

(5)

The firm fixed effects \( \zeta_j \) implicitly control for time-invariant characteristics such as sector and for pseudo-stable characteristics such as firm size. The inclusion of firm fixed effects implies that, if an intrinsically more volatile firm is added at some point in time, this shows up as a relatively high estimate for this firm’s specific effect without necessarily implying an increase in measured average volatility.

4 Results

This section discusses the results from the balanced panels of continuously available firms, both for the United States and for Japan.

\(^{16}\)We use heteroskedasticity-robust standard errors throughout the paper.
4.1 US firms

The upper left diagram of Figure U5 documents the evolution of US firm-level sales growth volatility over time. Net sales became gradually less volatile in the second half of the 1980s. Sales growth volatility remained low in the period 1990-1993. From 1994 onwards, volatility increased, peaking in 2000. After that, sales have gradually become more stable.

The top row of Table U1 summarizes the average volatility levels for the two ten-year periods in the sample, along with a standard error. The average standard deviation of the first-stage residuals was 13.36 in the subsample 1986-2005, while it increased to 16.22 in 1996-2005. This increase of 2.86 points in the standard deviations is statistically significant at the 1 percent level, with an F-statistic of 62.23.

The other diagrams of Figure U5 document that EBIT volatility and employment volatility have followed a quite similar overall pattern. The overall picture that emerges is that US firms became gradually more stable in the second half of the 1980s, they became more volatile in the 1990s, and stabilized again after 2000.

Profit and employment volatility increase from the first to the second half of the sample, and these increases are statistically significant at the 1% level.

When comparing the volatility patterns across variables, note that sales and EBIT volatility may be affected by the decline in the volatility of inflation in the United States, while employment volatility is not. In practice, this is unlikely to be important in our sample, since our results are robust to deflating the former two variables by the PPI.

Furthermore, bear in mind that the estimated level of volatility depends on the way in which we scale the growth rates. Recall that we compute EBIT growth with lagged sales in the denominator, as in equation (1). Since the value of sales tends to exceed EBIT, this often means that measured
EBIT growth is closer to zero than it otherwise would have been. Since EBIT growth is computed in a different way than the two other growth measures, our finding that EBIT growth appears to be less volatile than sales and employment growth is uninterpretable. However, since these considerations affect volatility at any point of time, the time-paths are not appreciably affected by this consideration.

Davis, Haltiwanger, Jarvis, Miranda (2006) report the volatility of publicly traded firms. Notwithstanding the differences in sample composition and methodology, our findings are not obviously at odds with those of Davis e.a. (2006). The only actual difference is that for listed firms, Davis e.a.’s preferred volatility measure barely declines during the second half of the 1980s, while our results suggest a more substantial decline. From that point on, the Davis e.a. results resemble a smoothed version of our volatility measure. In particular, Davis e.a. find that volatility is flat in the early 1990s, but increases from about 1993 until 1999. Volatility decreases in 2000 and in 2001, which is the last year of their sample.

4.2 Japanese firms

The upper left diagram of Figure J5 suggests that net sales growth volatility was high in Japan during the bubble period in the second half of the 1980s. It declined substantially in 1991, in the aftermath of the stock market crash. Subsequently, volatility remained at its new, lower level through 2005, with the exception of upward peaks in 1995 and 2000, and a low-volatility period in 1996-97. Another way to interpret the graph is that sales growth has followed a trend decline from 1987 through 1997, and has tended to increase through about 2002, after which it has been declining somewhat.

The top row of Table J1 indicates that the average standard deviation of the first-stage residuals was 9.72 in the subsample 1986-1995, while it declined to 7.55 in 1996-2005. This decline of 2.17
points in the standard deviation is statistically significant at the 1 percent level, with an F-statistic of 192.62.

In Japan, profit and employment volatility followed different paths than sales volatility did. The top right diagram of Figure J5 graphs the time-path of volatility in EBIT growth. From 1986 through 1998, EBIT volatility followed a slight downward trend, barely noticeable on the graph. Subsequently, volatility increased steeply until it reached its peak in 2002. After that, EBIT volatility has been decreasing steeply, although it had not quite reached its 1998 level by the end of our sample.

The bottom diagram of Figure J5 suggests that employment growth volatility stayed relatively constant through 1996. Volatility increases steeply in the period 1997-2002. After that, it declines substantially through the end of the sample. Recall from section 2.2 that we omit employment growth observations for 2000 and 2001.

Table J1 indicates that both profit and employment became more volatile from the first to the second half of the sample, an increase which was statistically significant at the 1% level.

In conclusion, we find that employment and EBIT growth volatility displayed relatively similar patterns. Both volatility measures have significantly increased from the first to the second half of the sample. On the other hand, sales growth volatility has tended to decrease. Throughout the sample, the ratio of sales growth volatility to either earnings or employment volatility has declined.

As in the United States, inflation has tended to become less volatile over the course of our sample. However, analogous to the US case, our results are robust to deflating sales and EBIT by the Japanese PPI.

Our paper is the first to document sales, earnings and employment volatility in Japan. However, Hamao, Mei, and Xu (2007) estimate the time-path of the idiosyncratic component of firm-level
stock return and stock turnover volatility over the period 1975-1999 for firms listed on the Tokyo Stock Exchange. Our results suggest that idiosyncratic sales growth volatility followed a relatively similar path in Japan as idiosyncratic stock return volatility did.

As in Hamao et al (2007), we find that firm-level volatility tends to be lower after the 1990 stock market crash than before. The most noteworthy difference is that, unlike idiosyncratic stock return volatility, idiosyncratic sales growth volatility does not display a temporary, sharp increase around the time of the stock market crash, but instead declines substantially in the immediate aftermath of the crash. Another difference is that, while sales volatility did increase around the time of the 1997 and 1998 financial crises, the increase is not nearly as steep, relative to past volatility changes, as the upward jump in idiosyncratic stock volatility. Hamao et al (2007) attribute the high levels of idiosyncratic stock return volatility from 1997 on to an increase in bankruptcies associated with the 1997 and 1998 banking crises. The fact that we detect a smaller increase in sales growth volatility should be seen in light of the fact that our volatility estimates do not account for entry or exit.

5 Robustness

5.1 Results by Firm Size and Sector

This subsection reports more disaggregate results obtained by subdividing the balanced panels of continuously available firms into firm size quartiles and sectors.

Turning first to US results, Figure U7 reports results by firm size quartile based on threshold sales-to-GDP ratios. The left column applies to the quartile of smallest firms, with columns further to the right pertaining to increasingly larger firms. The first-stage regression is as in

---

17 For the sample of continuously available firms, we divide all observations in the balanced panel for 1986-2005 into four quartiles according to firm size as measured by the sales-to-GDP ratio. Both for the United States and for Japan, results are similar when we measure firm size by the number of employees.
equation (3), except for the fact that we drop interaction terms involving firm size dummies.

Figure U7 indicates that, irrespective of firm size, volatility tended to decrease in the second half of the 1980s, increase in the 1990s, and decrease in the first half of the 2000s. For every of the three volatility variables, smaller firms prove to be more volatile than larger firms.

Next, we present results by sector. As in section 3, we divide firms into three broad categories: manufacturing, services broadly defined (i.e. including wholesale and retail trade), and other sectors.\footnote{In the sample of 588 firms, our manufacturing category contains 353 firms (7060 observations), all with a primary activity which belongs to the SIC division ‘manufacturing’. The category services contains 114 firms (2280 observations) which belong to the SIC divisions ‘services’, ‘retail trade’, and ‘wholesale trade’. The category ‘other’ contains the 121 firms (2420 observations) which belong to one of the following SIC divisions: ‘agriculture, forestry, and fishing’, ‘mining’, ‘construction’, ‘transportation, communications, electric, gas, and sanitary service’, and ‘finance, insurance, and real estate’.}

We estimate volatility for every sector using a variant of equation (3) as well as equation (4), the only difference being that we omit sector interaction terms from the first-stage regression.

For every volatility variable, the previous section’s results turn out to be representative for the manufacturing sector. The volatility paths are virtually identical.

In the broadly defined services sector, volatility tends not to vary as quickly over time as in the manufacturing sector. Sales growth volatility increases at a slow pace from the early 1990s through the end of the sample.

Sales and employment in other sectors are not particularly volatile in the first half of the sample. However, sales and employment volatility increase substantially around the period 1997-2000, when they reach similar levels as in the manufacturing sector. This result is driven by the 65 firms (out of 114) which operate in the two-digit SIC code ‘electric, gas, and sanitary services’. So far, we do not know the precise reason for the high volatility in the electricity and gas sectors in the late 1990s.
Turning our attention to Japan, the top row of Figure J7 graphs the results for net sales growth volatility. The volatility patterns are not precisely the same across size quartiles, but are still reasonably comparable to the overall result from section 4. Irrespective of firm size, volatility tends to be lower after the 1990 stock market crash than before, and volatility increases somewhat after the 1997/98 financial crises. At most points of time, sales volatility is higher for the first and second quartiles than for observations with above-median firm size.

The second row of Figure J7 suggests that section 4’s results for earnings growth volatility holds irrespective of firm size. That figure’s third row suggests that the overall increase in employment volatility has predominantly been driven by smaller firms. Curiously, larger Japanese firms tend to be more volatile than smaller ones in terms of employment.

Next, we briefly discuss Japan’s results by sector. We classify firms into three sectors as explained in section 3. Out of the 577 sampled firms, we assign 381 to the category manufacturing, 123 to the broadly defined services sector, and 73 to the category ‘other sectors’.\footnote{Recall that other sectors comprise the sectors education, utilities, health, financial services, transport, agriculture, and mining.}

Figure J6 reports the volatility patterns, with each column corresponding to a different sector. The findings are quite similar across sectors. At any rate, the findings from section 4 are representative for the manufacturing sector.

5.2 Evidence from unbalanced panels

Finally, we check robustness to using the full Worldscope samples for the United States and for Japan. In this case, we estimate equations (3) and (5).

Figure U8 graphs the volatility paths for the United States. Firms in the unbalanced panel are about twice as volatile as a typical firm in the sample of continuously available firms. Nevertheless, we again confirm the overall pattern of declining volatility in the 1980s, increasing volatility in the
1990s, and decreasing in the 2000s. One noteworthy difference is that the decrease in volatility after 2000 is more pronounced in the unbalanced panel. We attribute this to the fact that many firms delisted from the stock market in the aftermath of the stock market crash, and to the possibility that these firms were likely smaller and more volatile. In other words, the post-2000 decline in volatility in Figure U8 reflects in part a change in the composition of firms.

Partly as a result of the pronounced declines in volatility after 2000, it turns out that one cannot statistically reject the hypothesis that average sales volatility over the first half of the sample was equal to sales volatility in the second half of the sample. To see this, please refer to Table U2. The same holds true for employment volatility. However, there continues to be a statistically significant increase in profit volatility.

Figure J8 graphs the volatility paths for Japanese firms. Notice that, notwithstanding the substantial differences in sample composition, the results are comparable to those for the balanced panel of firms. Average volatility is higher in the full Worldscope sample than in the restricted sample of continuously available firms, but the difference is not nearly as stark as in the US case.

According to Table J2, the decline in sales growth volatility, as well as the increase in earnings and employment volatility, continue to be significant at the 1 percent level.

6 Conclusion and Interpretation

This paper has characterized earnings and employment volatility of US and Japanese firms using a new methodology. Like the predominant method, we compute the deviation of every firm’s growth rate from a medium-term average growth rate. However, based on the insight that this does not need to restrict us to computing medium-term average deviations, we develop a method that allows us to estimate a (standard) deviation for every year separately.

In the United States, we find that firms became gradually more stable in the second half of the
1980s, but became gradually more volatile in the 1990s, before stabilizing again after 2000.

Volatility is neither clearly pro-cyclical nor counter-cyclical. For instance, some adverse aggregate events coincide with high firm-specific volatility while other don’t.\(^\text{20}\) However, the pattern which emerges is that volatility tends to gradually decline in the aftermath of adverse aggregate events, while it gradually increases during protacted periods of stable growth. The Volcker disinflation, the 1987 stock market crash, and the 2000 stock market crash and recession all precede periods of a gradual decline in volatility. Meanwhile, volatility gradually increases during the productivity acceleration of the 1990s.

We interpret this pattern as plausibly reflecting time-varying risk awareness on behalf of company managers and investors, which influenced the actual degree of risk. Plausibly, firm managers’ beliefs about the distribution of risks depends heavily on recent outcomes. After an adverse tail event, managers will tend to assign a larger probability value to large negative shocks than they did before, even if there had been no change in the actual conditional risk distribution. This increased risk awareness would make managers less prone to undertake projects with a high actual degree of riskiness, as reflected in ex post volatility \(\sigma_{e,tt}\). As old projects run out and new ones get decided on, the average riskiness and realized volatility of projects would therefore gradually decrease in the aftermath of an adverse event.\(^\text{21}\)

\(^{20}\)The 1987 stock market crash did not coincide with an increase in idiosyncratic volatility. Likewise, the savings-and-loans crisis of the early 1990s did not noticeably increase firm-level volatility. The 2000 stock market crash and recession did coincide with a sharp but temporary increase in volatility. In unreported results based on firms for which data are available in 1981-1985, we find that the disinflation-induced recession of the early 1980s coincided with a period of high volatility.

\(^{21}\)In addition, an adverse macroeconomic event may cause investors to decrease their shareholdings of highly risky firms in particular. To see this, note that the ex ante risky firms are likely the most strongly affected during the economic downturn. Therefore, even if investors tend to hold well-diversified asset portfolios and are therefore indifferent to any changes in firm-specific volatility per se, they will tend to disinvest from risky companies because of their low (current and expected) profitability. The associated drop in share prices of the low-growth / high volatility firms may act as a signal to the managers of these firms to buy back shares and reduce the scale of the worst-performing projects. This would tend to reduce the fraction of volatile projects, implying a gradual decline in firm-level volatility.
In Japan, we find that sales growth volatility was high during the bubble years of the second half of the 1980s. The period 1991-1997 witnessed a gradual decline in sales growth volatility. During this period, the stock and real estate bubbles had burst, but authorities and financial institutions were reticent to recognize the underlying problem of deteriorating asset quality. As a result, resources continued to be allocated to stagnant, poorly performing firms. In other words, government involvement and financier behavior dampened the full impact of market forces on these firms, thereby largely preventing that risk materialized into observed volatility. This explains why volatility did not increase during that period. (Sales volatility in fact declined during that period.)

After the financial crises of 1997 and 1998, when several financial institutions failed and Japan’s lingering financial system imbalances came to the surface, sales volatility increased somewhat, and profit volatility increased markedly. This increase in volatility coincided with the deepest macroeconomic downturn. As our levels data show (see the upper right diagram of Figure J3), it also coincided with a period in which firms were struggling to remain profitable. This finding mirrors that of Hamao, Mei and Xu (2007) for stock market data, who attributed the rise in idiosyncratic stock market risk at that time to a rise in bankruptcies.

Another interpretation for the increase in firm volatility since the mid-1990s is that it reflects an increase in flexibility of the Japanese economy, which arguably occurred as a response to the crisis. One particular example of this is an increase in labor market flexibility. Morgan (2005) explains that from the mid-1990s on, Japanese firms increasingly hired flexible types of labor, such as part-time and temporary workers. Taken by itself, this development should have enabled firms to adjust their labor stock more flexibly in response to changes in idiosyncratic (and other) conditions, which could explain the observed increase in firm-specific employment volatility. All other things equal, increased flexibility should allow firms to better stabilize profits. Our results
suggest however that the observed increases in flexibility were not sufficient to allow firms to keep
profits stable in the face of the deep downturn of the late 1990s.
References


Appendix: Figures and tables

Figure U1

All US Firms: Mean and Quartiles of Levels Data

Notes: This figure documents the distribution of net sales, earnings and the number of employees in every year over the period 1986-2005 for all 15,425 firms in our US sample from Worldscope. Large diamonds indicate the median, while small diamonds indicate the 25th and 75th percentiles. The dashed line is the mean. Net sales and Earnings Before Interest and Taxes (EBIT) are in million USD. Employees stands for the number of employees.
Figure U2

All US Firms: Mean and Quartiles of Growth Rates

Notes: This figure documents the distribution of the growth rates of net sales, earnings and the number of employees in every year over the period 1986-2005 for all 15,425 firms in our US sample from Worldscope. Large diamonds indicate the median, while small diamonds indicate the 25th and 75th percentiles. All growth rates are in percentage terms.
Notes: This figure documents the distribution of net sales, earnings and the number of employees in every year for the 588 US firms in our Worldscope sample for which data are continuously available over the period 1986-2005. Other notes are as under Figure 1.
Figure U4
Balanced Panel US Firms: Mean and Quartiles of Growth Rates

Notes: This figure documents the distribution of the growth rates of net sales, earnings and the number of employees in every year for the 588 US firms in our Worldscope sample for which data are continuously available over the period 1986-2005. Other notes are as under Figure 2.
Figure U5

Balanced Panel US: Firm-Level Volatility

Notes: This figure graphs firm-level sales, earnings, and employment growth volatility for every year for the balanced panel of 588 US firms for which data are continuously available over 1986-2005, along with a 95 percent confidence interval. Volatility is estimated from equations (3) and (4). Figure U5 graphs the estimated time effects in the second-stage equation (4). See Table U1, below, for corresponding statistics.
Figure U6
Balanced Panel US: Firm-Level Volatility by Sector

Notes: This figure graphs firm-level sales, earnings, and employment volatility when subdividing the 588 US firms in the balanced panel into three broad sectors. The left column pertains to manufacturing firms, the middle column to service providers (including wholesalers and retail traders), and the third to firms in other sectors. Volatility for every sector is estimated using equations (3) and (4), with the only difference that sector dummies and sector interaction terms were omitted from the first-stage regression.
Figure U7
Balanced Panel US: Firm-Level Volatility by Firm Size Quartile

Notes: This figure graphs firm-level sales, earnings, and employment volatility when subdividing observations into size quartiles for 1986-2005 according to the sales-to-GDP ratio. The left column applies to the smallest firms, with columns further to the right pertaining to increasingly larger firms. Volatility for every size quartile is estimated using equations (3) and (4), with the only difference that firm size dummies and size interaction terms were omitted from the first-stage regression.
Figure U8

All US Firms: Firm-Level Volatility

Notes: This figure graphs firm-level sales, earnings, and employment growth volatility for all 15,425 US firms in our Worldscope sample for 1986-2005, along with a 95 percent confidence interval. Volatility is estimated with firm fixed effects in the second-stage regression, as in equation (5). See Table U2 for corresponding statistics.
### Table U1
Balanced Panel US: Firm-Level Volatility

<table>
<thead>
<tr>
<th></th>
<th>Average volatility 1986-1995</th>
<th>Average volatility 1996-2005</th>
<th>Change in volatility</th>
<th>F-statistic for significant change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales growth</td>
<td>13.36</td>
<td>16.22</td>
<td>2.86***</td>
<td>62.23</td>
</tr>
<tr>
<td></td>
<td>(0.24)</td>
<td>(0.27)</td>
<td>(0.36)</td>
<td>[0.00]</td>
</tr>
<tr>
<td>EBIT growth</td>
<td>5.93</td>
<td>7.07</td>
<td>1.13***</td>
<td>25.03</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.17)</td>
<td>(0.23)</td>
<td>[0.00]</td>
</tr>
<tr>
<td>Employment growth</td>
<td>12.65</td>
<td>14.51</td>
<td>1.86***</td>
<td>30.39</td>
</tr>
<tr>
<td></td>
<td>(0.22)</td>
<td>(0.25)</td>
<td>(0.34)</td>
<td>[0.00]</td>
</tr>
</tbody>
</table>

Notes: This table pertains to Figure U5. Standard errors of F-tests for significance are in round brackets, and p-values are in square brackets. The first column indicates average firm-level volatility over a first subsample (1986-1995), and the second indicates average volatility over the subsample 1996-2005. The third column reports the change in volatility from the first to the second subsample. *** indicates significance at the 1 percent level. The fourth column reports the F-statistic and p-value for the null hypothesis of no change in volatility between the two subsamples.

### Table U2
All US Firms: Firm-Level Volatility

<table>
<thead>
<tr>
<th></th>
<th>Average volatility 1986-1995</th>
<th>Average volatility 1996-2005</th>
<th>Change in volatility</th>
<th>F-statistic for significant change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales growth volatility</td>
<td>28.75</td>
<td>28.84</td>
<td>0.09</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td>(0.22)</td>
<td>(0.09)</td>
<td>(0.31)</td>
<td>[0.78]</td>
</tr>
<tr>
<td>EBIT growth volatility</td>
<td>23.01</td>
<td>24.72</td>
<td>1.71***</td>
<td>30.80</td>
</tr>
<tr>
<td></td>
<td>(0.22)</td>
<td>(0.09)</td>
<td>(0.31)</td>
<td>[0.00]</td>
</tr>
<tr>
<td>Employment growth volat.</td>
<td>21.95</td>
<td>21.83</td>
<td>-0.12</td>
<td>0.22</td>
</tr>
<tr>
<td></td>
<td>(0.18)</td>
<td>(0.08)</td>
<td>(0.26)</td>
<td>[0.64]</td>
</tr>
</tbody>
</table>

Notes: This table pertains to Figure U8. Standard errors are in round brackets, and p-values in square brackets. Other notes are as under Table U1.
Figure J1
All Firms: Mean and Quartiles of Levels Data

Notes: This figure documents the distribution of net sales, earnings and the number of employees in every year over the period 1986-2005 for all 4507 Japanese firms in the Worldscope database. Large diamonds indicate the median, while small diamonds indicate the 25th and 75th percentiles. The dashed line is the mean. Net sales and Earnings Before Interest and Taxes (EBIT) are in million USD. Employees stands for the number of employees.
Figure J2

All Firms: Mean and Quartiles of Growth Rates

Notes: This figure documents the distribution of the growth rates of net sales, earnings and the number of employees in every year over the period 1986-2005 for all 4507 Japanese firms in the Worldscope database. Large diamonds indicate the median, while small diamonds indicate the 25th and 75th percentiles. All growth rates are in percentage terms.
Figure J3
Balanced Panel: Mean and Quartiles of Levels Data

Notes: This figure documents the distribution of net sales, earnings and the number of employees in every year for the 577 Japanese firms in the Worldscope database for which data are continuously available over the period 1986-2005. Other notes are as under Figure 1.
Figure J4
Balanced Panel: Mean and Quartiles of Growth Rates

Notes: This figure documents the distribution of the growth rates of net sales, earnings and the number of employees in every year for the 577 Japanese firms in the Worldscope database for which data are continuously available over the period 1986-2005. Other notes are as under Figure 2.
Figure J5
Balanced Panel: Firm-Level Volatility

Notes: This figure graphs firm-level sales, earnings, and employment growth volatility for every year for the balanced panel of 577 Japanese firms for which data are continuously available over 1986-2005, along with a 95 percent confidence interval. Volatility is estimated from equations (3) and (4). Figure J5 graphs the estimated time effects in the second-stage equation (4). See Table J1, towards the end of the appendix, for corresponding statistics.
Figure J6
Balanced Panel: Firm-Level Volatility by Sector

Notes: This figure graphs firm-level sales, earnings, and employment volatility when subdividing the 577 Japanese firms in the balanced panel into three broad sectors. The left column pertains to manufacturing firms, the middle column to service providers (including wholesalers and retail traders), and the third to firms in other sectors, containing companies involved in education, utilities, health, financial services, transport, agriculture, and mining. Volatility for every sector is estimated using equations (3) and (4), with the only difference that sector dummies and sector interaction terms were omitted from the first-stage regression.
Notes: This figure graphs firm-level sales, earnings, and employment volatility when subdividing observations into size quartiles for 1986-2005 according to the sales-to-GDP ratio. The left column applies to the smallest firms, with columns further to the right pertaining to increasingly larger firms. Volatility for every size quartile is estimated using equations (3) and (4), with the only difference that firm size dummies and size interaction terms were omitted from the first-stage regression.
Figure J8
All Firms: Firm-Level Volatility

Notes: This figure graphs firm-level sales, earnings, and employment growth volatility for all 4507 Japanese firms in Worldscope for 1986-2005, along with a 95 percent confidence interval. Volatility is estimated with firm fixed effects in the first-stage regression, as in equation (5). See Table J2 for corresponding statistics.
### Table J1
Balanced Panel: Firm-Level Volatility

<table>
<thead>
<tr>
<th></th>
<th>Average volatility 1986-1995</th>
<th>Average volatility 1996-2005</th>
<th>Change in volatility</th>
<th>F-statistic for significant change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales growth</td>
<td>9.72 (0.11)</td>
<td>7.55 (0.11)</td>
<td>-2.17***</td>
<td>192.62</td>
</tr>
<tr>
<td>EBIT growth</td>
<td>2.48 (0.05)</td>
<td>3.71 (0.05)</td>
<td>1.23***</td>
<td>356.64</td>
</tr>
<tr>
<td>Employment</td>
<td>5.03 (0.10)</td>
<td>6.06 (0.12)</td>
<td>1.02***</td>
<td>42.75</td>
</tr>
</tbody>
</table>

Notes: This table pertains to Figure J5. Standard errors of F-tests for significance are in round brackets, and p-values are in square brackets. The first column indicates average firm-level volatility over a first subsample (1986-1995), and the second indicates average volatility over the subsample 1996-2005. For employment growth, the average of the second subsample is computed over eight years only, since employment growth observations for 2000 and 2001 were omitted. The third column reports the change in volatility from the first to the second subsample. *** indicates significance at the 1 percent level. The fourth column reports the F-statistic and p-value for the null hypothesis of no change in volatility between the two subsamples.

### Table J2
All Firms: Firm-Level Volatility

<table>
<thead>
<tr>
<th></th>
<th>Average volatility 1986-1995</th>
<th>Average volatility 1996-2005</th>
<th>Change in volatility</th>
<th>F-statistic for significant change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales growth</td>
<td>12.17 (0.10)</td>
<td>9.55 (0.06)</td>
<td>-2.62***</td>
<td>492.43</td>
</tr>
<tr>
<td>EBIT growth</td>
<td>3.01 (0.04)</td>
<td>4.25 (0.03)</td>
<td>1.24***</td>
<td>551.99</td>
</tr>
<tr>
<td>Employment</td>
<td>5.85 (0.09)</td>
<td>6.44 (0.06)</td>
<td>0.59***</td>
<td>28.30</td>
</tr>
</tbody>
</table>

Notes: This table pertains to Figure J8. Standard errors are in round brackets, and p-values in square brackets. Other notes are as under Table J1.