



The upward trend in the volatility of firm productivity shocks

Yunting Liu¹

Department of Finance, School of Economics, Peking University, Beijing, 100871, China

HIGHLIGHTS

- This paper documents robust evidence on the upward trend in the volatility of firmspecific productivity shocks.
- The trend is robust after controlling for the compositional change of the data sample.
- The upward trend is stronger for firms that are smaller, younger, and are in the technology sector.

ARTICLE INFO

Article history:

Received 18 October 2017
Received in revised form 20 November 2017
Accepted 21 November 2017
Available online 6 December 2017

JEL classification:
E2

Keywords:

Firm productivity shocks
Volatility
Upward trend

ABSTRACT

I document robust empirical evidence on the upward trend in the volatility of firm-specific productivity shocks. The trend is robust after controlling for the compositional change of the data sample and is stronger for firms that are newer, smaller and are in the technology sector.

© 2017 Elsevier B.V. All rights reserved.

1. Introduction

Researchers following the seminal contribution of Bloom (2009) attempt to understand the dynamics of the volatility of firm-specific productivity shocks and study the effects of this volatility on the aggregate economy.

This paper develops empirical methods to robustly quantify variations in the volatility of firm-specific productivity shocks. I find that there exists an upward trend in the volatility of firm-specific productivity shocks. The trend remains robust after controlling for the compositional change of the data sample. Moreover, the upward trend in the volatility of firm-specific productivity shocks is even stronger for firms that are younger, smaller, and in the technology sector. Thus, I argue that the upward trend in volatility is likely reflecting a fundamental change of the economy. This finding contributes to the literature on firm-level risk. While (Campbell et al., 2001; Comin and Mulani, 2006) discover the upward trend in the stock return and sales growth volatility, my paper provides evidence that the rise in the firm-level risk

may be driven by the increase in the volatility of productivity shocks.

Bloom et al. (2012) use the confidential Census Bureau data to measure the volatility of aggregate and plant-specific productivity shocks and find that both the aggregate and plant-specific volatility are countercyclical at the business cycle frequency. They measure the volatility of plant-specific productivity shocks as the cross-sectional dispersion of plant productivity shocks. It is important to note that the volatility at the plant level in the manufacturing sector reported by Bloom et al. (2012) is relatively stable.² Using firm-level data instead of plant-level data may be the reason why I find the upward trend.³

My empirical analysis complements (Bloom et al., 2012) in several ways. First, I robustly quantify the dynamics of firm-specific productivity shocks volatility, controlling for the compositional change of data sample and other firm characteristics. Second, I accommodate the estimation of firm production functions by employing the widely used Compustat database. In addition, I focus on

² Thanks for an anonymous referee pointing out.

³ The supplementary material discusses more about this issue. Understanding different dynamics at the plant and firm level might be useful for future research.

E-mail address: yuntingliu@pku.edu.cn.

¹ Assistant Professor.

the variation in firm-specific volatility at longer frequencies: the upward trend over the last five decades.

2. Empirical results

The section develops measures for the volatility of firm-specific productivity shocks and explores potential causes for its variation over time. The firm productivity is a standard measure for the overall effectiveness of the production process in which capital and labor are used. To be more specific, I estimate the production function given in

$$y_{i,t} = \beta_0 + \beta_k k_{i,t} + \beta_l l_{i,t} + \omega_{i,t} + \eta_{i,t} \quad (1)$$

where $y_{i,t}$ is the log of sales for firm i in period t ; $k_{i,t}$ and $l_{i,t}$ are log values of capital stock and labor input used in the production, respectively. The firm productivity is denoted by $\omega_{i,t}$ and $\eta_{i,t}$ represents the error term unknown by the firm and the econometrician. The parameters β_l and β_k are to be estimated and the method of estimating firm-level productivity adopts from Olley and Pakes (1996), which has been used by Imrohoroglu and Tüzel (2014) recently. This semi-parametric method is advocated because it is able to control for simultaneity and selection bias. A selection problem is generated by the relationship between productivity and the shutdown decision, and a simultaneity problem is produced by the relationship between productivity and input demands. The details of this estimation method are provided in the supplementary material.

Following Bloom et al. (2012), firm-specific productivity shock is estimated based on the following first order autoregressive equation about log productivity ($\omega_{i,t}$).

$$\hat{\omega}_{i,t+1} = \rho_\omega \hat{\omega}_{i,t} + \mu_i + \lambda_{t+1} + \epsilon_{i,t+1} \quad (2)$$

where $\hat{\omega}_{i,t}$ denotes the estimated log productivity. The specification controls for the firm fixed effect: μ_i and the time fixed effect: λ_t . The log firm productivity is estimated for a panel of firms using data from Compustat. The data spans annually from 1963 to 2015.

2.1. Cross-Sectional measure of firm-specific productivity shocks volatility

Following Bloom et al. (2012), the benchmark firm-specific volatility measure $\sigma_{\epsilon,t}$ is defined to be standard deviation of firm-specific productivity shocks $\epsilon_{i,t}$ across firms at a given time t . Fig. 1 plots the time-series of the volatility of firm-specific productivity shocks. The underlying data frequency is annual. A salient feature of the graph is the upward trend in the level of firm-specific productivity shock volatility, which has more than doubled in the last fifty years.

2.2. An alternative way to measure the volatility of firm-specific productivity shocks

An relevant question is whether the change in the volatility of firm-specific productivity shocks measured in Section 2.1 are due to changing characteristics of the data sample. One way to control for the composition effect is to look at changes in the volatility of productivity shocks at the firm level. I obtain firm-specific productivity shocks $\epsilon_{i,t}$ at date $t - 1, t, t + 1$ for a given firm. Squaring them and taking the difference produce a (very noisy) measure of the change in firm i 's volatility of firm-specific productivity shocks from date t to $t + 1$. Let $\Delta Vol_{i,t+1} \equiv \epsilon_{i,t+1}^2 - \epsilon_{i,t}^2$ denotes this change. For each date $t + 1$, I calculate $\Delta Vol_{t+1,EW}$: the equal-weighted mean of the change of volatility across all firms with non-missing $\Delta Vol_{i,t+1}$. Similarly, I produce value-weighted

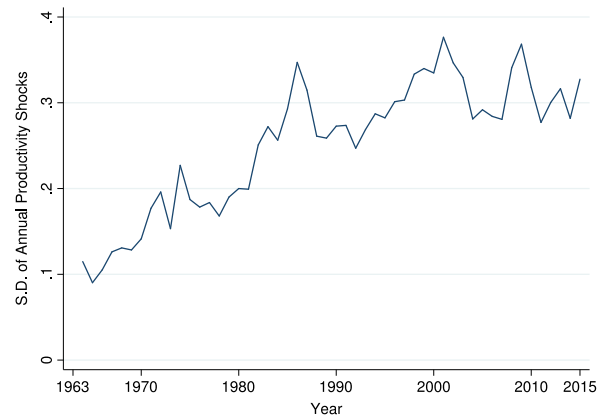


Fig. 1. The volatility of firm-specific productivity shocks. This figure plots the time-series of annual firm-specific productivity shocks volatility constructed by using the Compustat dataset. The sample spans from 1963 to 2015. The volatility is defined as the cross-sectional dispersion of annual productivity shocks across firms.

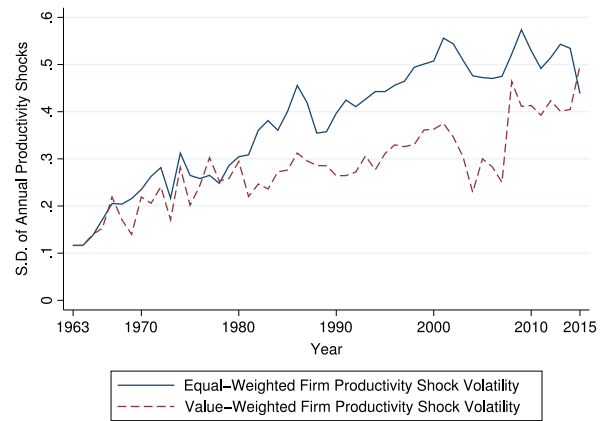


Fig. 2. The volatility of firm-specific productivity shocks using a time-series method. This figure plots the time-series of annual firm-specific productivity shocks volatility by using the method in Section 2.2. I use the Compustat and CRSP datasets from 1963 to 2015. The dotted line gives the value-weighted firm-specific volatility measure, which weights changes of firm productivity by firm market equity values. The solid line plots the equal-weighted measure.

mean using market equity value at time t , which is denoted by $\Delta Vol_{t+1,VW}$. The last step is to keep track of the level of volatility from the change of volatility over time. Let $Vol_{t,EW} \equiv \sum_{s=1}^t Vol_{s,EW}$ and $Vol_{t,VW} \equiv \sum_{s=1}^t Vol_{s,VW}$ denote these measures for the level of firm-specific volatility.

Fig. 2 plots the time-series of these estimates from 1963 to 2015. It is clear from Figs. 1 and 2 that there exists a robust upward trend in the level of firm-specific volatility.

2.3. Rolling window measure of the volatility of firm-specific productivity shocks

Another way of measuring the volatility of firm-specific productivity shocks is by focusing on the time series. Formally, I consider the rolling time series measure for the volatility of $\epsilon_{i,t}$ as

$$VolR_{i,t} = \sqrt{\frac{\sum_{\tau=t-g}^t (\epsilon_{i,\tau} - \bar{\epsilon}_{i,t})^2}{10}} \quad (3)$$

where $\bar{\epsilon}_{i,t} \equiv \sum_{\tau=t-g}^t \epsilon_{i,\tau}$. When computing the standard deviation in the time series, I remove the average productivity shock for the firm in the window, and in effect control for firm-specific

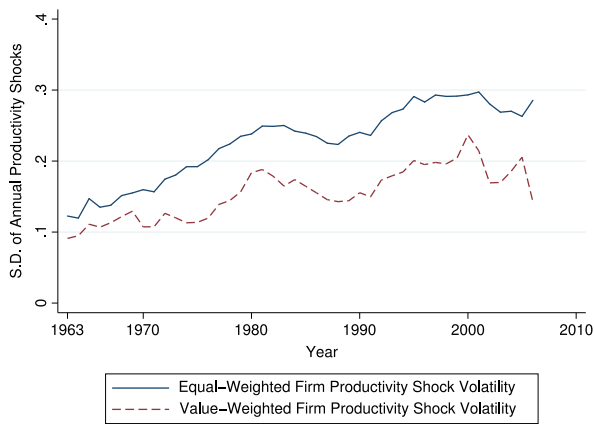


Fig. 3. The volatility of firm-specific productivity shocks using rolling S.D. This figure plots the time series of annual firm-specific productivity shocks volatility by using rolling-window standard deviations method in Section 2.3. The data spans from 1963 to 2015 using Compustat database.

aspects that affect firm productivity shock. These aspects, however, potentially show up in the cross-sectional measure and may be the medium through which a compositional bias operates. These standard deviations are then averaged across all the firms in a year to arrive at an annual volatility. As illustrated in Fig. 3, this volatility at the firm level also exhibits a significant upward trend.

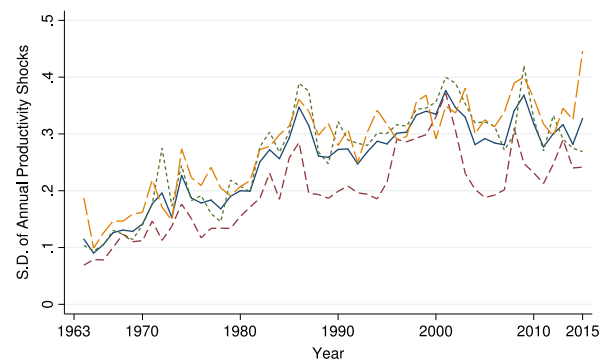
2.4. Controlling for firm size, age and sectors

I have presented three different measures for the volatility of firm-specific productivity shocks. Since the time series of all measures display the same upward trend, I focus on the first measure: the cross-sectional dispersion $\sigma_{\epsilon,t}$ hereafter. Fig. 4 exhibits the time-series of the volatility for firms with different sizes, ages and that are in different sectors. In each year, I divide firms into three groups based on their market capitalization or ages. I also examine four main industries in this paper: consumer goods, manufacturing, health products and information, computer and technology industries. Classifications of sectors are defined in the supplementary material.

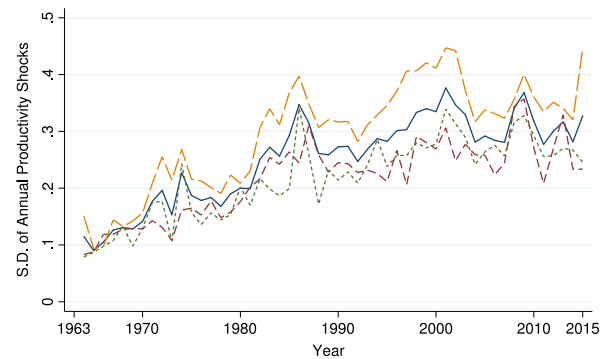
We can directly see from Fig. 4 that the upward trend in volatility holds for firms with different characteristics. In particular, the trend increase is stronger for small firms and weaker for large firms. Younger firms have a stronger increase in the productivity shocks volatility, while older firms go through a relatively milder increase. Among sectors, the information technology sector witnesses the strongest increase in the volatility of firm-specific productivity shocks. The peak volatility is 0.54 in year 2001 while the highest volatility for all sectors is 0.38 in the same year. The consumer goods sector takes the smallest increase in volatility with the peak of 0.28 in year 2012.

3. Conclusion

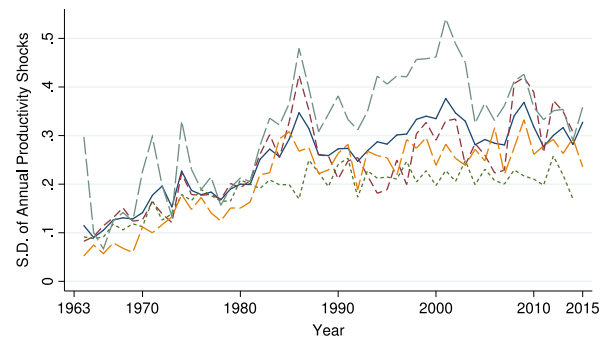
This paper documents a substantial and robust upward trend in the volatility of firm-specific productivity shocks over the last fifty years. The rise in volatility is robust after controlling for the compositional change of the data sample. This finding suggests that this change in the volatility of firm-specific productivity shocks may be due to a fundamental change of the economy. Understanding causes and consequences of this trend could be a fruitful avenue of future research.



(a) Controlling for size.



(b) Controlling for age.



(c) Controlling for sectors.

Fig. 4. The volatility of firm-specific productivity shocks controlling for size, age and sectors. This figure plots the time series of the volatility of annual firm-specific productivity shocks for firms with different sizes, ages and that are in different sectors. The volatility is measured as the cross-sectional dispersion of annual firm-specific productivity shocks. The sample spans from 1963 to 2015. I consider manufacturing, consumer goods, health products and information technology sectors.

Acknowledgments

This paper is based on part of Chapter 2 of my dissertation at the Johns Hopkins University. I am indebted to Greg Duffee for his invaluable suggestions. I am also thankful for helpful comments

from an anonymous referee. Research support from School of Economics, Peking University is gratefully acknowledged. The usual disclaimer applies.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.econlet.2017.11.027>.

References

- Bloom, N., 2009. The impact of uncertainty shocks. *Econometrica* 77 (3), 623–685.
- Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., Terry, S.J., 2012. Really Uncertain Business Cycles. Working Paper 18245. National Bureau of Economic Research.
- Campbell, J.Y., Lettau, M., Malkiel, B.G., Xu, Y., 2001. Have individual stocks become more volatile? an empirical exploration of idiosyncratic risk. *J. Finance* 56 (1), 1–43.
- Comin, D., Mulani, S., 2006. Diverging trends in aggregate and firm volatility. *Rev. Econ. Stat.* 88 (2), 374–383.
- Imrohorglu, A., Tüzel, S., 2014. Firm-Level productivity, risk, and return. *Manage. Sci.* 60 (8), 2073–2090.
- Olley, G.S., Pakes, A., 1996. The dynamics of productivity in the telecommunications equipment industry. *Econometrica* 64 (6), 1263–1297.