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Cross-Sectoral Variation in Firm-Level Idiosyncratic Risk

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In this paper we use data from the U.S. Census Bureau's Longitudinal Research Database in order to assess the extent of the cross–sectoral variation in firm–level idiosyncratic risk and shed light on its determinants. We find that firms producing investment goods exhibit greater volatility in sales and TFP growth than firms producing consumption goods. Our data suggests that this may be the case because winner–takes–all competition is more common for the former than for the latter.

Key words: Firm-Level Risk, Product Turnover, R&D Intensity.

JEL code: L16, L60, O30, O31, 040.

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1 Introduction

In this paper we estimate firm–level idiosyncratic volatility in sales and in total factor productivity across manufacturing firms in the Census' Longitudinal Research Database (LRD). No matter the measure of risk, we find that firms producing investment goods exhibit systematically higher idiosyncratic risk than their counterparts producing consumption goods.

We argue that this is the case because investment sectors are more likely to be characterized by Schumpeterian competition. In such industries, firms are constantly involved in technological races. When at the lead of the race, a firm can generate sizeable economic profit, at the expense of its competitors. However, as one or more such competitors innovate and take the lead, revenues abruptly fall. This conjecture is motivated by two findings: volatility tends to be higher in sectors where product turnover and R&D intensity are higher.

Given their inability to completely diversify it away, the decisions of all stakeholders to a firm depend on the magnitude of the idiosyncratic risk it faces. This is the case for managers and employees, as well as customers, suppliers, and financiers, such as banks, bondholders, and equityholders. These considerations implies that the new fact we document will be of interest to most applied microeconomists.

Our findings are also necessary inputs for research in asset pricing, international trade, economic development, and all other fields that model the equilibrium interaction between firms facing different levels of idiosyncratic risk. For example, Castro, Clementi, and MacDonald (2008) and Cuñat and Melitz (2007) argue that cross–sectoral differences in idiosyncratic risk, together with cross–country heterogeneity in institutions, may be the cause of the cross–country variation in relative price of capital goods and investment rate (the former), and trade specialization (the latter). Caggese (2008) models the impact of idiosyncratic risk on the propensity to innovate of entrepreneurial firms.

Our paper contributes to a small, but fast increasing literature interested in assessing volatility at the firm level. However, most of this literature has focused on *time* variation, rather than cross–sectional variation. Using returns from CRSP, Campbell, Lettau, Malkiel, and Xu (2001) found that the average variance of single–stock returns has more than doubled during the period 1962–1997, in spite of the fact that the market as a whole has not become more volatile. Comin and Mulani (2006) and Comin and Philippon (2005) reported that the mean volatility of sales growth for COMPUS-

TAT firms has also been increasing throughout the whole post–WWII period, in spite of the decline in business cycle volatility. Consistently, Davis, Haltiwanger, Jarmin, and Miranda (2006) showed that the volatility of employment growth for public firms in the Census Bureau's Longitudinal Business Database (LBD) has also increased. However, this result does not extend to the whole sample, for which average volatility of employment growth has actually decreased.

The cross–sectional variation of idiosyncratic risk is the object of interest for Campbell, Lettau, Malkiel, and Xu (2001) and Michelacci and Schivardi (2008), who exploited data on stock returns to assess the variation in firm–level risk across industries in the U.S. and in a variety of other countries, respectively. To date, the study that is closest to ours is by Castro, Clementi, and MacDonald (2008), who documented the cross–sectoral variation in sales growth volatility among COMPUSTAT firms. They find investment good firms to be significantly riskier than consumption good firms. These results are confirmed by Cuñat and Melitz (2007), who conduct a similar exercise on the same data.

We improve on Castro, Clementi, and MacDonald (2008) along several dimensions. First, we show that their main empirical result still holds for firms in the LRD, a much larger dataset, representative of the entire US manufacturing sector. Since COMPUSTAT only includes companies whose stock is traded in an organized exchange, one could not rule out that their finding was simply the outcome of selection. We can.

Second, we show that a similar cross–sectoral distribution of idiosyncratic risk emerges when we measure risk as the volatility of TFP growth. Given poor data on capital, estimating TFP is rather problematic with COMPUSTAT, and therefore was not an option for Castro, Clementi, and MacDonald (2008). It is much less of an issue with the LRD. The conditional volatility of sales growth is not the ideal proxy for idiosyncratic risk because swings in a firm's sales depend not only on the shocks which size we are interested in measuring, but also on the firm's ability to alter its inputs to accommodate them. The volatility in firm–level TFP growth is not subject to the same criticism.

Finally, and perhaps most importantly, we make progress towards understanding the determinants of the cross–sectoral variation we document. Exploring the correlates of our estimates of idiosyncratic risk, we find that the most volatile sectors are characterized by more frequent product turnover and higher R&D intensity. This evidence is consistent with the conjecture that in most investment goods sectors, firms are engaged in a constant technological race. They are hit by large shocks whenever their products become leaders in their markets or when are made obsolete by the introduction of new products by their competitors.

The remainder of the paper is organized as follows. The data and our methodology are described in Section 2. Our estimates are illustrated in Sections 3 and 4. In Section 5 we document the positive association between our measures of risk and proxies for product turnover and R&D intensity. Finally, Section 6 concludes.

2 Data and Methodology

2.1 Data

Our data is from the Annual Survey of Manufactures (ASM) portion of the Longitudinal Research Database (LRD) for the years 1972 through 1997. In every year, our sample size varies between 50,000 and 70,000 establishments, distributed among 140 three–digit SIC manufacturing industries. With the ASM weights, our sample ends up being representative of the entire U.S. manufacturing sector.

Real sales are nominal value of shipments, deflated using the four–digit industry–specific deflator from the NBER manufacturing productivity database. Size is measured by the number of employees, whereas age is the time since the establishment started production.[1]

Note that our unit of observation is an establishment, defined as the minimal unit where production takes place. This is obviously short of ideal, as multi–plants firms may change the assignment of production to plants in response to shocks. In spite of this caveat, in the remainder, we will use *plant* and *firm* interchangeably.

As briefly recalled in the introduction, using the LRD rather than COMPUSTAT has a variety of advantages. Since our sample is representative of the entire U.S. manufacturing sector, our results are not subject to the selection bias emphasized by Davis, Haltiwanger, Jarmin, and Miranda (2006), who document a behavior of public firms markedly different from that of private firms. Furthermore, the LRD allows for a finer level of disaggregation. Given its size, we can conduct our analysis at the 3–digit SIC sectoral level, which map into 4– and 5–digit NAICS. Working with COMPUSTAT, Castro, Clementi, and MacDonald (2008) could not go finer than 3—digit NAICS.

[1] In our regression analysis, we follow Davis, Haltiwanger, and Schuh (1996) in that we use 3 categories of age dummies: Young, Middle-Aged, and Mature.

The only drawback from using the LRD is that we restrict ourselves to manufacturing firms, whereas COMPUSTAT spans all sectors.[2]

2.2 Methodology

We obtain our estimates of sales growth volatility by means of a two–step regression procedure. In the first step, we estimate

$$\Delta \ln(sales)_{ijt} = \mu_i + \delta_{jt} + \beta_{1j} \ln(size)_{ijt} + \beta_{2j} Age_{ijt} + \varepsilon_{ijt}. \tag{1}$$

The dependent variable is the growth rate of real sales for firm i in sector j, between years t and $t+1$. The dummy variable μ_i is a firm–specific fixed effect that accounts for unobserved long–run heterogeneity across firms. The variable δ_{jt} denotes a full set of sector–specific year dummies, which control for changes in sales induced by sector–specific shocks and cross–sectoral differences in business cycle volatility. We include size and age because both were shown to be negatively correlated with firm growth.[3]

The purpose of regression 1 is to decompose firm growth into a systematic, or predictable component, and a component capturing idiosyncratic risk. Any variation in sales growth not due to systematic factors is captured by the estimated residuals of (1), $\hat{\varepsilon}_{ijt}$, and is interpreted as being due to firm–specific shocks.

The second step entails measuring how the standard deviation of such shocks varies across sectors. This is accomplished by fitting a simple log–linear model to the variance of residual sales growth:

$$\ln \hat{\varepsilon}^2_{ijt} = \theta_j + v_{ijt}, \tag{2}$$

where θ_j is a sector dummy. Letting $\hat{\theta}_j$ denote its point estimate, $\sqrt{\exp(\hat{\theta}_j)}$ is our measure of the conditional standard deviation of sales growth for firms in sector j.

3 Results

For each 3–digit industry, Table 5 reports the the estimated volatility. The range of estimates is rather wide. With a 0.5% estimated residual volatility, firms producing Bakery Products (SIC 205) appear to be the least risky. On the other end of the

[2] The Longitudinal Business Database (LBD), also from the Census Bureau, has information for firms in all industries. However, since it does not contain information on capital stocks, it is not suited to computing firm–level TFP.

[3] See **?** and **?**.

spectrum are manufacturers of railroad equipment (374), whose volatility is estimated at a whopping 18.53%.

3.1 Consumption Vs. Investment Goods

Given the results of Castro, Clementi, and MacDonald (2008), we find it natural to ask our data whether investment good firms are riskier than consumption good firms.

To classify sectors as consumption or investment good producing, we rely on the 1992 BEA's Use Input–Output Matrix. The Use Matrix provides information on the amount of output that each sector provides as input to other sectors, as well as to final demand uses. For each three-digit SIC industry, we compute the share of a sector's output whose ultimate destination is either a consumption or an investment final demand use. We label an idustry as "consumption" or "investment" if a sufficiently large share of its production ultimately goes to a consumption or to an investment use, respectively. See Appendix A.2 for details.

We then run the following regression:

$$\ln \hat{\varepsilon}_{ijt}^2 = \alpha + \theta_C + u_{ijt}, \tag{3}$$

where α is a constant and θ_C is a consumption good dummy. We are interested in testing whether this dummy is significantly negative. Our results are illustrated in Figure 1. The height of each bar reflects the volatility of one three–digit sector.

According to Figure 1, investment good sectors are among the most volatile in the economy. This observation is confirmed by the estimates of regression (3). The consumption dummy coefficient is negative and highly significant. It is equal to -0.3682, with a p–value smaller than 0.0001. The regression constant is -4.3968 and also significantly different from zero. These numbers imply average sales growth volatilities of 11.098% for investment good firms and of 9.232% for consumption good firms.

3.1.1 Durable Vs. Non–Durable Consumption Goods

In Section 5 we will ask whether our data sheds any light on the determinants of the cross–sectoral variation documented above. Towards that end, we find it of interest to assess whether firms producing durable consumption goods are more volatile than those producing nondurables. This analysis is prompted by the fact that durables sectors share potentially relevant features with investment sectors. Namely, they exhibit similar product turnover rates and R&D intensity.

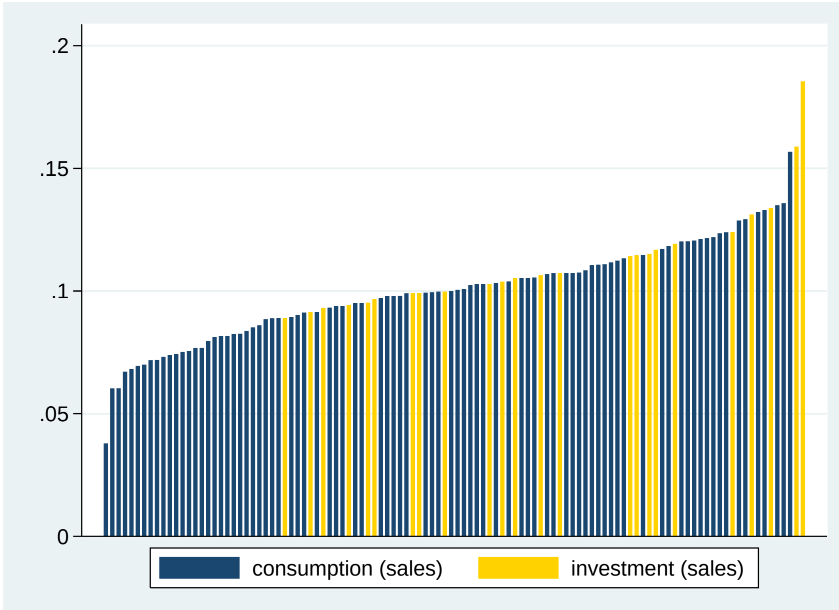

Figure 1: Volatility of sales growth per 3–digit industry.

We classify consumption goods as durables if they have a service life of 3 years or more, and nondurable otherwise. The service life data is from Bils and Klenow (1998). We drop sectors for which they do not provide information. The details of the assignment procedure are in Appendix A.3.

Figure 2 hints that firms producing durables are among the riskiest in the economy, just like those producing investment goods. For each of the three aggregates – investment, durable consumption, and nondurable consumption – we define a synthetic volatility measure as the weighted average of the volatility coefficients of the 3–digit industries that compose it. The weights are the shares of each industry's value of shipments in the total for the aggregate. The measures are 11.659%, 9.871 % and 9.115% for investment, durables, and nondurables, respectively.[4]

4 Volatility of Firm–Level TFP Growth

Since firms are likely to respond to shocks by optimally adjusting their inputs, it is likely that those reported above are upward–biased estimates of idiosyncratic risk.

In this Section we consider an alternative measure of risk, the volatility in firm–level TFP growth, which is not subject to the caveat just described. Following the

[4]The next time we gain access to the LRD data set, we will test statistically the hypothesis that firms producing durables and nondurables have different volatilities.

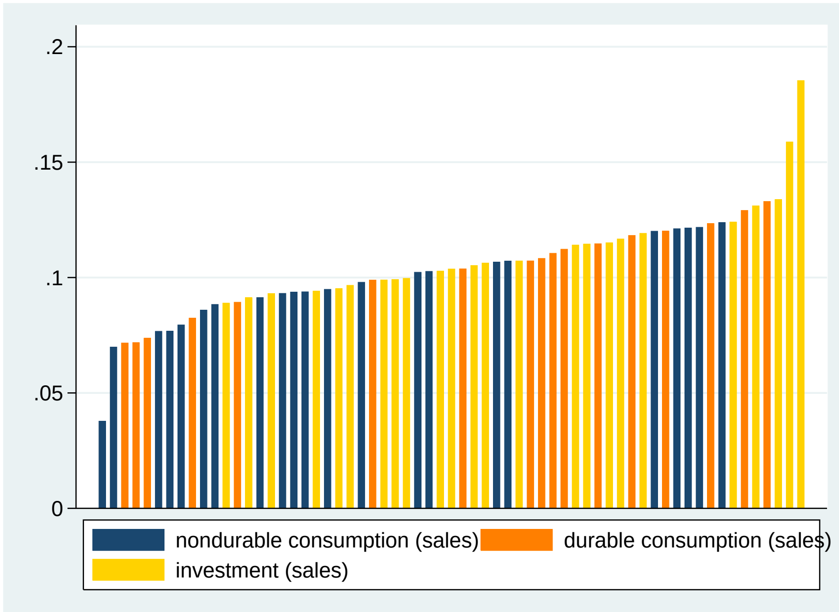

Figure 2: Volatility of sales growth per 3–digit industry.

literature,[5] we define firm–level TFP levels as firm–level Solow residuals. The (log) Solow residual for firm i in sector j at time t is

$$\ln z_{ijt} = \ln y_{ijt} - \alpha_j^k \ln k_{ijt} - \alpha_j^\ell \ln \ell_{ijt} - \alpha_j^m \ln m_{ijt},$$

where y_{ijt} is shipments, k_{ijt} is capital, ℓ_{ijt} is labor, and m_{ijt} is materials. The elasticities α_j^k, α_j^ℓ and α_j^m are assumed to be sector–specific. As in the literature just cited, we set them equal to narrowly–defined sectoral input cost shares. Further details are contained in Appendix A.1.

Figure 3 illustrates the sectoral ranking of our idiosyncratic risk measures. The estimates are reported in Table 5.

Displaying a clear tendency for investment good sectors to be among the most volatile, Figure 3 confirms the results obtained with sales growth. A formal test based on (3) provides further support. The consumption dummy coefficient is again negative and highly significant. It is equal to -0.2208, with a p-value smaller than 0.0001. The regression constant is -5.0773, also significantly different from zero at a high confidence level. These figures imply average volatilities of 7.897% for investment good firms and of 7.072% for consumption good firms. As expected, these estimates

[5]See Foster, Haltiwanger, and Krizan (2001), Baily, Hulten, and Campbell (1992), and Syverson (2004).

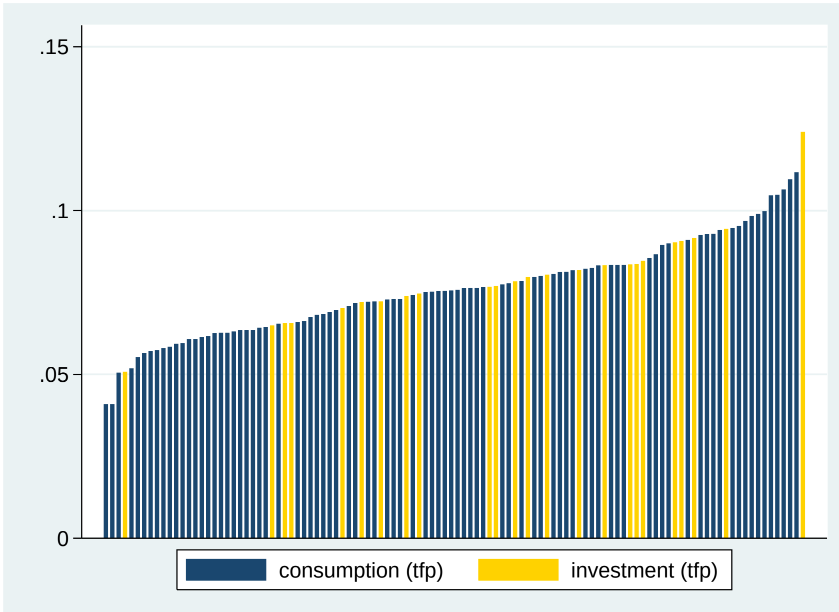

Figure 3: Volatility of tfp growth per 3–digit industry.

are smaller than those obtained in Section 3. Interestingly, the same holds for their difference.

Figure 3 displays the results when consumption goods category are split between durables and nondurables. Based on the figure alone, it is not possible to discern whether firms in durable consumption sectors are riskier.

The weighted averages of the volatility coefficients reported in Table 5 are 8.523%, 7.405% and 7.246% for investment, durable consumption, and nondurable consumption, respectively.

5 Determinants of Firm–Level Risk

The finding that firms producing capital goods and consumption durables tend to face higher risk leads us to ask which distinguishing features of these sectors are likely to be the direct cause of the greater risk. In this section we investigate the correlates of our volatility measures with proxies of product turnover and R&D intensity.

Product turnover is emphasized in Schumpeterian, or quality-ladder growth models, as in Grossman and Helpman (1991) and Aghion and Howitt (1992). In this type of model, firms' investment in R&D lead to improvements in product quality (or production techniques). The adoption of an innovation allows a firm that is behind

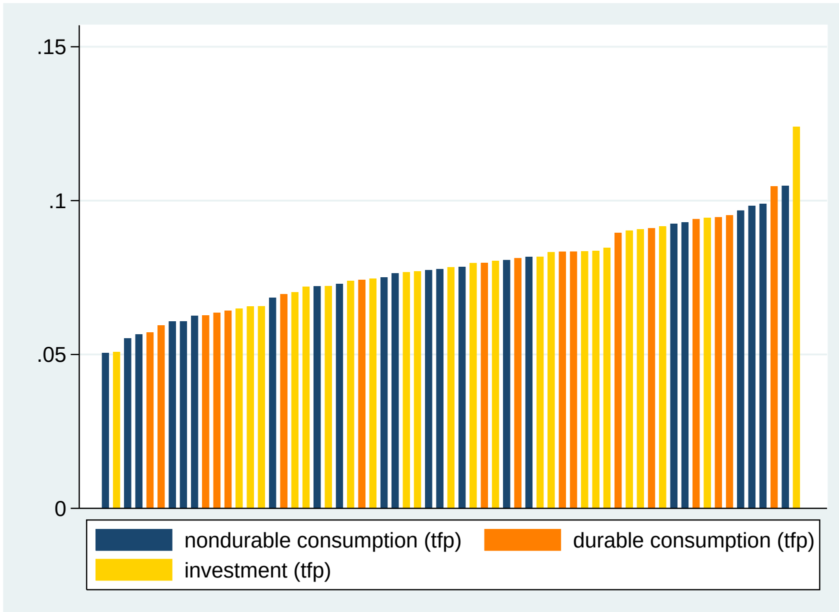

Figure 4: Volatility of tfp growth per 3–digit industry.

to advance to the frontier and steal the business of its competitors. Competitors are forced to reduce the price of their products, or exit the market, at least until they introduce a new better product. More frequent changes in the ladder are then associated with higher rates of product turnover. Our goal is to see whether industries with higher rates of product turnover are also the ones we identified previously as having higher idiosyncratic risk.

5.1 Product Turnover

As a measure of the importance of such innovation in the product space, we use information on the frequency of product turnover in each sector.

The BLS collects prices on 70,000–80,000 non–housing goods and services from around 22,000 outlets across various locations. When an item is discontinued, the BLS starts collecting prices of a closely related item at the same outlet, and records the item substitution information. This information is then used to compile the Commodities and Services Substitution Rates. Our data is drawn from Bils and Klenow (2004)'s tabulations, which are based on information gathered from 1995 to 1997.[6]

[6]Bils and Klenow (2004) also reports noncomparable item substitution rates across the main consumer good categories (called ELI, or entry–level items). Average item substitution rates and noncomparable average item substitution rates are highly correlated across ELIs. The results did not change much when we used noncomparable item substitution rate instead.

For 53 manufacturing sectors, we were able to match the SIC code with the entry–level items (ELIs).[7] For 21 goods, each ELI corresponds to a three–digit SIC industry. For 213 goods, multiple ELIs belong to one three-digit SIC industry. In this case, the CPI weights from the BLS are used to calculate the average item substitution rates.

Before proceeding, we mention two caveats. First, since the BLS CPI data focuses on consumer goods, many investment good sectors are missing. Second, the substitution rate only tells about the "frequency" of the product turnover and does not provide information about the "size of the step", the extent to which a new product improves over the old, existing product.

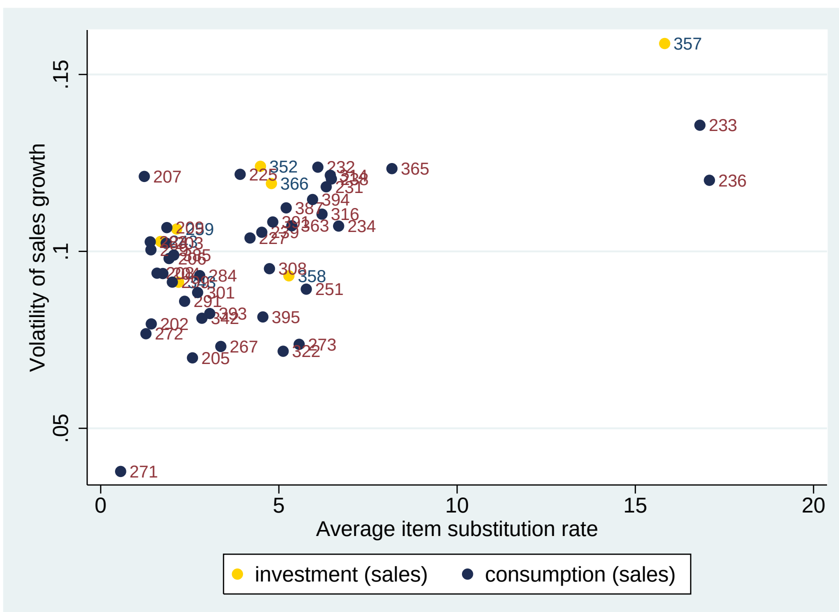

Figure 5: Volatility of sales growth and product substitution rate.

Figure 5 is the scatter plot of 3–digit SIC industries along the dimensions of sales growth volatility and substitution rates. The two variables are positively associated, with a simple correlation coefficient of 0.543. After excluding 3 obvious outliers – Computer and Office Equipment (357), Women's and Misses' Outerwear (233), and Girls' and Children's Outerwear (236) – the correlation drops to 0.359.[8] The positive correlation between the two variables strongly suggests that on average firms in industries with higher product turnover are subject to greater idiosyncratic risk.

Table 1 reports the results of regressing sales growth volatility on the average

[7] We thank Yongsung Chang for providing the bridge between the SIC code and ELI.
[8] Figure 7 in the Appendix excludes the outliers.

Table 1: Sales Volatility and Substitution Rate

Dependent Variable: Sales volatility	(1) w. outliers	(2) w. outliers	(3) w/o outliers	(4) w/o outliers
Substitution Rate	0.0031***	0.0030***	0.0034**	0.0039**
	(0.0007)	(0.0008)	(0.0013)	(0.0016)
Durable		-0.0019		-0.0048
		(0.0063)		(0.0072)
Investment		0.0107		0.0072
		(0.0078)		(0.0082)
Constant	0.0870***	0.0872***	0.0862***	0.0855***
	(0.0038)	(0.0046)	(0.0052)	(0.0058)
Observations	53	45	50	43
R^2	0.295	0.301	0.129	0.164

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

substitution rate. Column (1) implies that on average a 1% higher substitution rate implies a 0.31% higher volatility of sales growth. Neither the coefficient of the substitution rate nor the R^2 changed much after the durable consumption dummy and investment good dummy were added (column (2)). This suggests that product turnover basically captures all the cross–sectoral differences in firm–level risk that we previously identified with good types. When the three outlier sectors are dropped (columns (3) and (4)), the coefficient increases but the R^2 is reduced by a half.

Figure 6 and Table 2 illustrate the results of the same analysis, when using TFP growth volatility as risk measure. The correlation between substitution rate and risk proxi is now 0.571, about the same magnitude as above. Removing the three outlier lowers the correlation to 0.235. When product turnover is accounted for, the durable and investment dummies cease to explain cross–sectoral variation in firm-level risk. On average, a 1% higher average substitution rate implies about 0.25% higher TFP growth volatility. The coefficient did not change much after dropping the outliers. However, a substantially lower R^2 suggests that product turnover has less explanatory power for firm–level TFP volatility than for firm–level sales volatility.

5.2 R&D Intensity

As an alternative measure of the importance of innovation, we calculate research intensity from COMPUSTAT. We measure research intensity of each sector by dividing

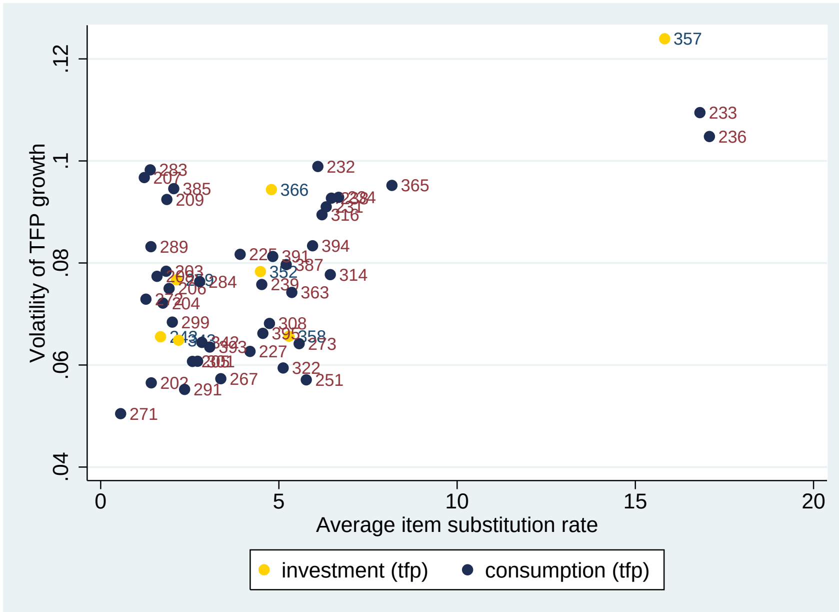

Figure 6: Volatility of TFP growth and product substitution rate.

Table 2: TFP Volatility and Substitution Rate

Dependent Variable: **TFP volatility**	(1) w. outliers	(2) w. outliers	(3) w/o outliers	(4) w/o outliers
Substitution Rate	0.0025***	0.0026***	0.0016	0.0021*
	(0.0005)	(0.0006)	(0.0009)	(0.0012)
Durable		-0.0054		-0.0044
		(0.0047)		(0.0054)
Investment		-0.0006		-0.0030
		(0.0058)		(0.0061)
Constant	0.0666***	0.0684***	0.0697***	0.0703***
	(0.0028)	(0.0034)	(0.0039)	(0.0043)
Observations	53	45	50	43
R^2	0.326	0.304	0.055	0.073

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

R&D expenditure by sales of the 3-digit SIC industry.[9]

Table 3 reports the results of regressing sales growth volatility on the research

[9]Since this measure is based on COMPUSTAT firms, the sources skew heavily toward larger firms. Our measure of research intensity varies from 0.15% (201, Meat Products) to 7.85% (274, Miscellaneous publishing) in the sample.

intensity. Column (1) implies that on average a 1% increase in research intensity is associated with a 9.79% higher volatility of sales growth. Once we include the durable consumption dummy and investment good dummy, the coefficient drops to 2.45%. Here, unlike the case of product turnover in section 5.1, investment good dummy is statistically significant.

Table 3: Sales Volatility and Research Intensity

Dependent Variable:	**Sales volatility**	
	(1)	(2)
R&D Intensity	0.0979	0.0246
	(0.1225)	(0.1273)
Durable		0.0036
		(0.0064)
Investment		0.0112**
		(0.0054)
Constant	0.0997***	0.1007***
	(0.0031)	(0.0039)
Observations	108	78
R^2	0.006	0.059

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

When TFP growth volatility is used as risk measure, R&D intensity seems to play a more important role in explaining cross–sectoral variation in firm-level risk. Table 4 illustrates the results of the same regression analysis, when using TFP growth volatility as firm-level idiosyncratic risk. The results in columns (1) and(2) suggests that a 1% higher average research intensity implies about $21-22\%$ higher TFP growth volatility. In column (2), the durable and investment dummies increase the fit of the regression but are not statistically different from 0.

6 Conclusion

This paper provides sectoral estimates of firm–level idiosyncratic risk among U.S. manufacturing firms. Consistently with Castro, Clementi, and MacDonald (2008), we find that on average firms producing investment goods face higher idiosyncratic risk than those producing consumption goods.

Our analysis also identifies one likely determinant of the cross–sectoral variation we document. We find that both of our volatility measures are strongly positive

Table 4: TFP Volatility and Research Intensity

Dependent Variable:	**TFP volatility**	
	(1)	(2)
R &D Intensity	0.2110**	0.2234**
	(0.0832)	(0.0857)
Durable		-0.0016
		(0.0043)
Investment		0.0001
		(0.0036)
Constant	0.0723***	0.0737***
	(0.0021)	(0.0026)
Observations	108	78
R^2	0.057	0.086

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

correlated with proxies of product turnover and R&D intensity. We interpret this as evidence that sectors with relatively high volatility are likely to be characterized by Schumpeterian competition.

A Data and Measurement

A.1 Variable Definitions

Real Sales or Output. We use the total value of shipments (TVS) deflated by the four–digit industry-specific shipments deflator from the NBER manufacturing productivity database. Although it is possible to adjust total shipments for the change in inventories, we follow Baily, Bartelsman, and Haltiwanger (2001) in imputing inventories for some plants (in particular, the smaller ones). To avoid potential measurement issues associated with this imputation, we focus on gross shipments.

Capital. We follow Dunne, Haltiwanger, and Troske (1997) closely in constructing capital stocks. The approach is based on the perpetual inventory method. We define the initial capital stock as the book value of structures plus equipment, deflated by the BEA's two–digit industry capital deflator. In turn, book value is the average of beginning-of-year and end-of-year assets. The investment series are from the ASM, deflated with the investment deflators from the NBER manufacturing productivity database (Bartelsman and Gray, 1996). Two–digit depreciation rates are also obtained from the BEA.

Labor input. The labor input is measured as the total hours of production and nonproduction workers. Since the latter are not actually collected, we follow Baily, Hulten, and Campbell (1992) in assuming that the share of production worker hours in total hours equals the share of production workers wage payments in the total wage bill.

Materials. The costs of materials are deflated by the material deflators from the NBER manufacturing productivity database.

Factor Elasticities. We use four–digit industry–level revenue shares as factor elasticities. This procedure implicitly assumes that all plants in each narrowly defined industry operate the same production technology, a common assumption in the literature on plant–level productivity. In calculating labor's share of total costs, we follow Bils and Chang (2000) and adjust each four–digit industry's wage and salary payments by a factor that captures all the remaining labor payments, such as fringe benefits and employer Federal Insurance Contribution Act (FICA) payments. This factor is based on information from the National Income and Product Accounts (NIPA), and corresponds to one plus the ratio of the additional labor payments to wages and salaries at the two–digit industry level. We apply the same adjustment factor to all firms within the same two–digit industry.

ASM sample weights. For all plant–level regressions, we use the ASM sample weights, which render the ASM a representative sample of the population of manufacturing plants (Davis, Haltiwanger, and Schuh, 1996).

A.2 Definition of Consumption and Investment Categories

To assign sectors to the consumption and investment categories, we rely on the Bureau of Economic Analysis' (BEA) 1992 Benchmark Input–Output Use Summary Table (before redefinitions) for Six–Digit Transactions. The 1992 Use Table is based on the 1987 SIC system, and thus compatible with the ASM.

The Use Table gives the fraction of output that each three–digit sector supplies to every other three-digit industry, as well as directly to final demand uses. The final demand uses correspond to NIPA categories. For each three–digit industry j, we define its final demand for consumption $C(j)$ as the sum of personal, federal, and state consumption expenditures. The final demand for investment $I(j)$ is defined analogously. We exclude imports, exports, and inventory changes from our definitions, since they are not broken down into consumption and investment. Let C and I denote the vectors of all the industries' final consumption and investment expenditures, respectively.

From the Use Table, we also compute the (square) matrix A of unit input–output coefficients. This matrix can be easily constructed from the original Use Input–Output Matrix by normalizing each row by the total commodity column. We can then define the vectors of all the industries' total consumption and total investment output by

$$Y_C = AY_C + C \Leftrightarrow Y_C = (I - A)^{-1} C$$

and

$$Y_I = AY_I + I \Leftrightarrow Y_I = (I - A)^{-1} I,$$

respectively. This means that each industry's consumption goods output also includes all the intermediate goods whose *ultimate* destination is final consumption. Similarly, for investment.

For each three–digit industry j, we compute the share of output destined to consumption, $Y_C(j)/ (Y_C(j) + Y_I(j))$. We then assign all industries with a share greater than or equal to 60% to the consumption good sector, and those with a share lower than or equal to 40% to the investment good sector. We discard the remaining industries.

We also discard industries whose primary role is supplying intermediate inputs to other industries. That is, we drop three–digit industries which contribute less than 1% of their total output directly to final consumption and investment expenditures.

A.3 Definition of Durable and Nondurable Consumption Categories

When splitting consumption sectors between durable and nondurable, we follow Bils and Klenow (1998). Table 2 of their study reports the service life of 57 consumption good items (those in the Consumer Expenditure Surveys that closely match four–digit SIC sectors). Their estimates are either based upon life expectancy tables from insurance adjusters, or upon the Bureau of Economic Analysis publication *Fixed Reproducible Tangible Wealth, 1925–1989*.

We classify goods as either durable on nondurable, depending on whether their expected lives are longer or shorter than 3 years. We classify each three–digit sector as producing durables or nondurables, according to the weighted average of its four–digit sub–sectors' expected lives. Finally, we drop those three–digit sectors that are not considered in Bils and Klenow (1998).

B Tables and Graphs

Table 5: Estimates (Sales and TFP growth)

SIC	Sales Volatility	Ranking (sales)	TFP volatility	Ranking (TFP)
		Investment Sectors		
243	0.10280	62	0.06554	103
245	0.13110	13	0.05076	130
252	0.09415	89	0.07019	88
254	0.10374	59	0.07390	77
259	0.10632	51	0.07670	62
324	0.08890	103	0.08350	37
325	0.09898	75	0.08172	47
327	0.11510	32	0.07967	55
328	0.10721	48	0.09065	25
343	0.09128	97	0.06487	105
344	0.11675	31	0.07699	61
352	0.12404	16	0.07832	57
353	0.13379	9	0.08360	36

Table 5: (continued)

SIC	Sales Volatility	Ranking (sales)	TFP volatility	Ranking (TFP)
354	0.10524	56	0.08463	34
355	0.11449	34	0.08322	41
356	0.09665	83	0.07220	81
357	0.15876	2	0.12395	1
358	0.09309	94	0.06565	102
361	0.09918	74	0.07199	84
362	0.09969	70	0.07462	75
366	0.11918	26	0.09439	15
374	0.18537	1	0.09023	26
381	0.11408	35	0.09154	22
382	0.09520	86	0.08039	52
		Durable Consumption Sectors		
227	0.10379	58	0.06267	113
231	0.11826	27	0.09100	24
251	0.08932	102	0.05710	126
273	0.07374	123	0.06419	107
274	0.07167	126	0.08340	38
316	0.11053	42	0.08945	28
322	0.07177	125	0.05942	121
348	0.12910	14	0.10458	8
363	0.10724	46	0.07423	76
365	0.12339	18	0.09520	13
375	0.12012	24	0.09396	16
379	0.13299	11	0.06957	90
385	0.09895	76	0.09457	14
387	0.11230	37	0.07968	54
391	0.10831	44	0.08127	49
393	0.08243	113	0.06352	109
394	0.11467	33	0.08337	40
		Nondurable Consumption Sectors		
201				
202	0.07950	117	0.05650	127
203	0.10232	66	0.07838	56
204	0.09375	92	0.07213	83
205	0.06991	127	0.06070	119
206	0.09798	77	0.07500	73
207	0.12118	21	0.09674	12

Table 5: (continued)

SIC	Sales Volatility	Ranking (sales)	TFP volatility	Ranking (TFP)
208	0.09384	91	0.07738	60
209	0.10673	50	0.09245	21
211				
212	0.09491	88	0.06254	115
213	0.07677	118	0.08065	51
225	0.12179	19	0.08169	48
232	0.12381	17	0.09891	10
234	0.10716	49	0.09287	19
236	0.12010	25	0.10478	7
271	0.03780	133	0.05047	131
272	0.07673	119	0.07291	79
283	0.10269	65	0.09825	11
284	0.09316	93	0.07635	65
291	0.08590	108	0.05521	128
299	0.09132	96	0.06841	96
301	0.08837	106	0.06074	118
314	0.12151	20	0.07772	59
		Other Consumption Sectors (no service life information)		
214	0.15666	3	0.09972	9
221	0.10063	67	0.07074	87
222	0.08886	104	0.05795	124
223	0.09795	78	0.07520	72
224	0.08507	110	0.06589	101
226	0.11155	39	0.07652	63
228	0.10274	64	0.06134	117
229	0.09926	73	0.07291	78
233	0.13566	7	0.10947	5
235	0.10723	47	0.08120	50
237	0.06940	128	0.04087	133
238	0.12047	22	0.09271	20
239	0.10541	53	0.07578	67
244	0.09968	71	0.06894	92
249	0.10526	55	0.07621	66
261	0.07413	122	0.07279	80
262	0.06812	129	0.05839	123
263	0.06706	130	0.06347	111
265	0.06024	131	0.04087	132
267	0.07314	124	0.05732	125
275	0.07514	121	0.06162	116

Table 5: (continued)

SIC	Sales Volatility	Ranking (sales)	TFP volatility	Ranking (TFP)
276	0.06022	132	0.05176	129
277	0.08253	112	0.08657	30
278	0.07535	120	0.06266	114
279	0.08157	114	0.08247	44
281	0.11076	40	0.10638	6
282	0.09113	98	0.07219	82
286	0.09712	81	0.08541	32
287	0.13484	8	0.11162	4
289	0.10044	68	0.08320	42
302	0.13218	12	0.08337	39
305	0.08365	111	0.07169	85
306	0.08877	105	0.06351	110
308	0.09511	87	0.06815	97
311	0.11066	41	0.07547	70
313	0.11712	28	0.05930	122
315	0.10528	54	0.08004	53
317	0.12864	15	0.08220	45
319	0.10306	61	0.08991	27
321	0.09015	100	0.07555	68
323	0.09988	69	0.06740	99
341	0.09936	72	0.06542	104
342	0.08111	116	0.06443	106
346	0.09790	80	0.06303	112
369	0.10743	45	0.07637	64
395	0.08148	115	0.06620	100
396	0.11319	36	0.07537	71

B.1 Figures

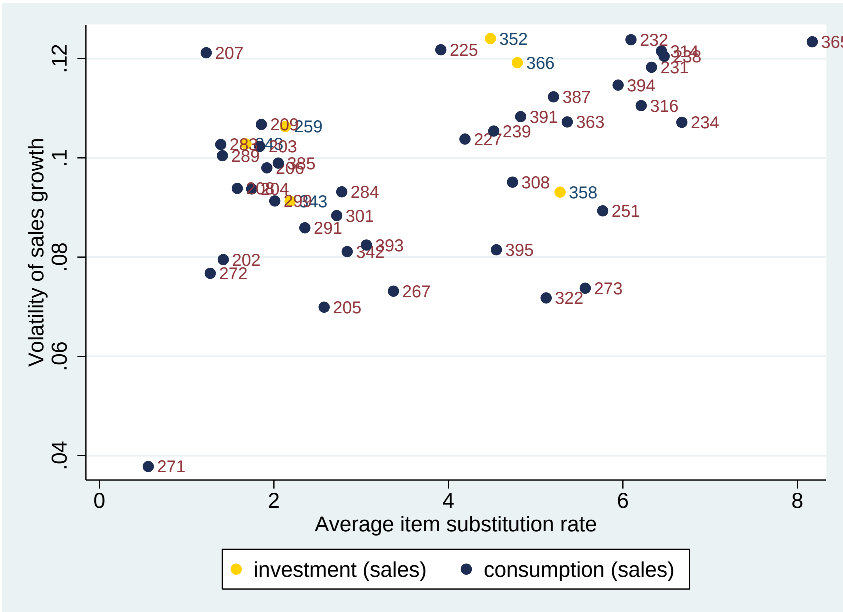

Figure 7: Volatility of sales growth and product substitution rate, excluding outliers.

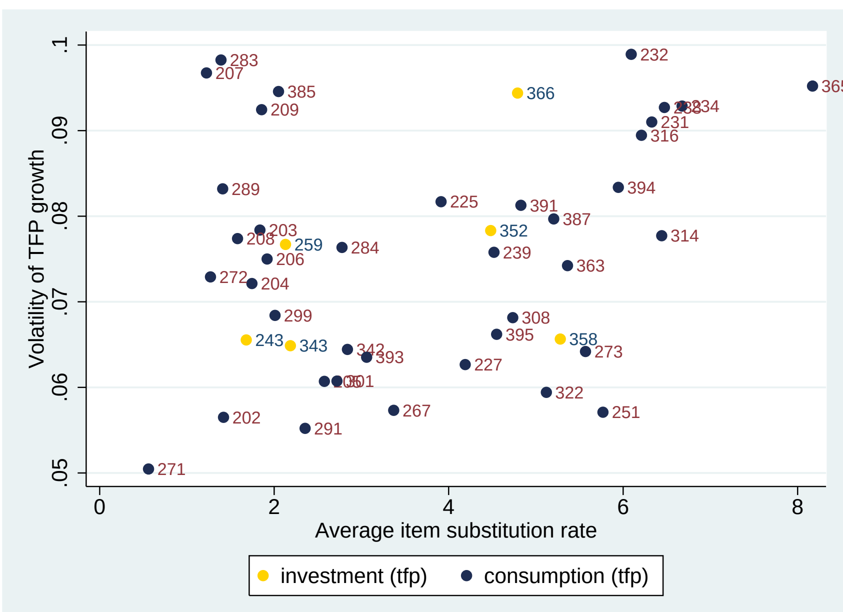

Figure 8: Volatility of TFP growth and product substitution rate, excluding outliers.

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