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CROSS-SECTORAL VARIATION IN THE VOLATILITY OF PLANT-LEVEL IDIOSYNCRATIC SHOCKS

Rui Castro
Gian Luca Clementi
Yoonsoo Lee

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ABSTRACT

We estimate plant--level idiosyncratic risk in the U.S. manufacturing sector. Our proxy for risk is the volatility of the portion of TFP growth which is not explained by either industry- or economy-wide factors, or by establishments' characteristics systematically associated with growth itself. Consistent with previous studies, we find that idiosyncratic shocks are much larger than aggregate random disturbances, accounting for about 90% of the overall uncertainty faced by plants. The extent of cross-sectoral variation in idiosyncratic risk is remarkable. Plants in the most volatile sector are subject to at least three times as much uncertainty as plants in the least volatile. Our evidence indicates that idiosyncratic risk is higher in industries where the extent of creative destruction is likely to be greater.

Rui Castro
Department of Economics
University of Montreal
Montreal H3C3J7 CANADA
rui.castro@umontreal.ca

Gian Luca Clementi
Department of Economics
Stern School of Business
New York University
44 West Fourth Street
New York, NY 10012
and NBER
clem@nyu.edu

Yoonsoo Lee
Department of Economics
Sogang University
Seoul, 121-742, Korea
ylee@sogang.ac.kr

1 Introduction

The main goal of this study is to assess the cross–sectoral variation in plant–level idiosyncratic risk in U.S. manufacturing. Our data consists of a large panel extracted from the Annual Survey of Manufacturers (ASM), gathered by the US Census Bureau.

We proxy idiosyncratic risk with the portion of the variation in the growth of Revenue Total Factor Productivity (TFPR) which cannot be forecasted by means of factors, either known or unknown to the econometrician, that are systematically related to plant dynamics.

Consistent with previous studies, our manufacturing–wide estimates suggest that idiosyncratic risk is much larger than aggregate risk. Our measure of the former accounts for roughly 90% of overall plant–level uncertainty.

The variation in idiosyncratic risk across three–digit industries is substantial. To gain a flavor of the amount of heterogeneity we uncover, consider that the volatility of TFPR growth due to idiosyncratic shocks ranges from 4.09% for producers of fur goods to a whopping 12.39% for manufacturers of computer equipment.

Why does volatility differ so much across sectors? We provide some preliminary evidence in favor of a particular explanation: volatility is higher in sectors where creative destruction is more important.

The notion of creative destruction is central to the Schumpeterian paradigm. According to the latter, firms are engaged in a perpetual race to innovate. Creation, i.e. the success by a laggard in implementing a new process or producing a new good, displaces the previous market leader, eliminating (destroying) its rent.

Formal models of Schumpeterian competition[1] predict a positive cross–sectoral association between creative destruction, product turnover, and innovation–related activities. We document that idiosyncratic risk is higher in industries where product turnover is greater and investment–specific technological progress is faster.

Over the last 25 years or so, a substantial body of research has documented a wide heterogeneity in the *level* of total factor productivity across plants. See Bartelsman and Doms (2000) and Syverson (2011) for a very effective account of this literature.

This paper is about the variation in the growth of productivity, rather than the level. Using US Census data, Davis and Haltiwanger (1992) and Davis, Haltiwanger, and Schuh (1996) documented a remarkable extent of within–sector job reallocation across manufacturing plants, while Davis, Haltiwanger, Jarmin, and Miranda (2006)

[1] We refer to the economic growth literature that builds on Aghion and Howitt (1992).

found a very wide variation in the volatility of business growth rates. Work by Bartelsman and Dhrymes (1998), Baily, Hulten, and Campbell (1992), Baily, Bartelsman, and Haltiwanger (2001) and Foster, Haltiwanger, and Krizan (2001) shows that such heterogeneity is accompanied by a substantial variation in productivity growth.

Our contribution to the literature is twofold. To start with, we strive to asses the portion of volatility in plant–level productivity growth that is due to merely idiosyncratic shocks. As indicated above, our proxy for volatility is the fraction of the variation in TFPR growth which is not accounted for by aggregate and industry-wide disturbances, or by plant-specific characteristics that are systematically associated with changes in productivity itself. Furthermore, we illustrate the cross–sectoral variation in plant–level idiosyncratic shocks. We provide estimates of risk by three–digit SIC sectors and make a first attempt at identifying the determinants of the heterogeneity we uncover.

Three other unpublished papers, by Abraham and White (2006), Gourio (2008), and Bachman and Bayer (2011), share our goal of estimating processes for plant– or firm–level idiosyncratic shocks. Their data is from the U.S. Census' LRD, Deutsche Bundesbank's USTAN, and Compustat, respectively. Beyond the data source, our work differs from theirs in the restrictions imposed on the stochastic process and in the emphasis we place on the cross–sectoral heterogeneity in risk.[2]

We are not the the first to document the extent of cross–sectoral variation in volatility. However, data considerations limit the analysis of previous studies to the variation of sales growth across large firms. See Chun, Kim, Mork, and Yeung (2008), Castro, Clementi, and MacDonald (2009), and Cuñat and Melitz (2010).[3]

For our purposes, the conditional volatility of sales growth is short of ideal. Swings in sales depend not only on idiosyncratic shocks, whose size we are interested in measuring, but also on the management's ability to alter the scale and input mix in order to accommodate them. This implies that residual volatility in sales growth is likely to be an upward–biased estimate of idiosyncratic risk. Our research confirms that this is indeed the case.

When we conduct our analysis substituting sales growth for TFPR growth, we find

[2] Campbell, Lettau, Malkiel, and Xu (2001) are also concerned with assessing idiosyncratic risk. Their proxy for the latter, however, is quite different. They decomposed the volatility of excess stock returns in three components: aggregate, industry–wide, and firm–level. This allowed them to obtain average measures of idiosyncratic risk for the whole economy and for several coarsely defined sectors. Their methodology delivers reasonable proxies for the risk borne by equity investors, but not for that faced by other stakeholders, such as the owners of small firms.

[3] In the cross–country study by Michelacci and Schivardi (2012), the proxy for risk is built following the methodology of Campbell, Lettau, Malkiel, and Xu (2001).

that the mean standard deviation of the residuals across all manufacturing plants is 10.07%, larger than above. The range of sectoral estimates is also wider. The ordering of sectors by volatility, while broadly consistent with that produced by TFPR, is not quite the same.

Our data has other advantages. Given the sample size, it allows us to work with a very fine sector classification. Furthermore, the sampling technique ensures that it is representative of the population of manufacturing plants.

Learning about the magnitude of plant–level idiosyncratic risk is important in light of the remarkable role that the latter plays in many areas of applied economics. In Hopenhayn (1992) and Ericson and Pakes (1995), two of the most popular frameworks for the study of industry dynamics, as well as in theories of financing constraints based on asymmetric information, such as Clementi and Hopenhayn (2006) and Quadrini (2003), firms are modeled as risk–neutral agents facing sequences of idiosyncratic shocks.

Given that firms' stakeholders have often limited insurance opportunities, assessing firm–level risk is also relevant for the analysis of scenarios where risk aversion matters. This is the case of entrepreneurship studies such as Quadrini (1999), theories of economic development such as Castro, Clementi, and MacDonald (2004, 2009), and models of innovation such as Caggese (2012).

The evidence of lack of risk diversification abounds. Herranz, Krasa, and Villamil (2009) find that 2% of the primary owners of the firms sampled by the 1998 Survey of Small Business Finance[4] invested more than 80% of their personal net worth in their firms; 8% invested more than 60%, and about 20% invested more than 40%. Clementi and Cooley (2009) document that in 2006, more than 20% of CEOs of U.S. publicly–traded concerns[5] held more than 1% of their companies' common stock. About 10% held more than 5%. Given the large capitalization of such companies, this information points to limited portfolio diversification for these individuals.

Understanding how idiosyncratic risk varies across industries is a necessary step towards the quantitative evaluation of a recent breed of multi–sector models, such as Castro, Clementi, and MacDonald (2009), Cuñat and Melitz (2010), and Caggese

[4]The SSBF, administered by the Board of Governors of the Federal Reserve System, surveys a large cross–sectional sample of non–farm, non–financial, non–real estate firms with less than 500 employees.

[5]The data is from EXECUCOMP, a proprietary database maintained by Standard & Poor's that contains information about compensation of up to 9 executives of all companies quoted in organized exchanges in the U.S.

(2012). According to the first two, cross–sectoral differences in idiosyncratic risk, together with cross–country heterogeneity in institutions, rationalize the observed cross–country variation in relative price of capital goods and investment rate (the former), and trade specialization (the latter). Caggese (2012) studies the impact of idiosyncratic risk on entrepreneurial firms' propensity to innovate.

The remainder of the paper is organized as follows. The data and methodology are described in Section 2. Our volatility estimates across three–digit industries are illustrated in Sections 3. In Section 4 we provide evidence in support of the conjecture that idiosyncratic risk is greater in industries where creative destruction is more important. In Section 5 we show that, consistent with what found by Castro, Clementi, and MacDonald (2009) for public firms, plants that produce capital goods are systematically riskier than their counterparts producing consumption goods. Finally, Section 6 concludes.

2 Data and Methodology

2.1 Data

We use the Annual Survey of Manufactures (ASM) and the Census of Manufacturers for the years 1972 through 1997. Our unit of observation is the establishment, defined as the minimal unit where production takes place. Depending on the year, our data comprises from 50,000 to 70,000 establishments, distributed among 140 three–digit SIC manufacturing industries.

The main reasons for choosing the ASM are that (i) it allows us to compute reliable estimates of plants' capital stocks, which are needed in order to compute our indicators of total factor productivity and that (ii) working with a panel rather than simply a cross–section, we are able to use fixed effects to control for unobserved plant characteristics.

The ASM allows for a fine level of disaggregation. Our analysis is at the three–digit SIC sectoral level, which maps into four– and five–digit NAICS. With respect to Castro, Clementi, and MacDonald (2009) and Comin and Philippon (2005), whose analysis is based on COMPUSTAT, 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, absent in COMPUSTAT.

The main drawback is that the ASM only covers manufacturing sectors. The

Census Bureau's Longitudinal Business Database (LBD) has a broader coverage. However, since it does not contain information on capital stocks, it is not suited to computing plant–level TFP.

2.2 Methodology

Our measure of productivity is what in the literature is known as real revenue per unit input, or Revenue Total Factor Productivity (TFPR). The (log) TFPR for plant 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 real sales, 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. Real sales are the nominal value of shipments, deflated using the four–digit industry–specific deflator from the NBER manufacturing productivity database. This is also the approach followed by Foster, Haltiwanger, and Krizan (2001), Baily, Hulten, and Campbell (1992), and Syverson (2004a) among others. All details can be found in Appendix A.1.

As effectively pointed out by Foster, Haltiwanger, and Syverson (2008), changes in the TFPR indicator reflect fluctuations in productive efficiency, as well as plant–specific shocks to input and output prices. This definition is well suited for our study, as we are interested in identifying all sources of idiosyncratic uncertainty, including price variation.

TFPR growth is in part the result of observable changes in the plant's environment, such as variations in aggregate demand. It is also affected by managerial choices, which in turn depend upon aggregate, industry–wide, and plant–specific characteristics.

Our objective is to measure what portion of the volatility of TFPR growth cannot be accounted for by either of these elements. As pointed out above, this is motivated by our desire to isolate and measure random disturbances.

We first compute the portion of TFPR growth which cannot be forecasted by means of factors, either known or unknown to the econometrician, which are systematically related to plant dynamics. We consider the following model:

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

The dependent variable is the growth rate of TFPR for plant i in sector j, between years t and $t+1$.[6] The dummy variable μ_i is a plant–specific fixed effect that accounts for unobserved persistent heterogeneity across plants. The variable δ_{jt} denotes a full set of sector–specific year dummies, which control for 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 plant growth.[7] Size is measured by the number of employees, whereas age is the time since the establishment went into operation.[8]

The objects of interest are the estimated residuals $\hat{\varepsilon}_{ijt}$, as they capture any variation in TFPR growth which is not due to systematic factors. We will interpret them as realizations of plant–specific shocks.

Recall that our main interest lies in characterizing the extent to which the standard deviation of such shocks varies across sectors. We satisfy our curiosity by fitting a simple log–linear model to the variance of the residuals. We posit that

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

where θ_j is a sector–specific dummy variable. Letting $\hat{\theta}_j$ denote its point estimate, $\sqrt{\exp(\hat{\theta}_j)}$ is our measure of the conditional standard deviation of TFPR growth for plants in sector j. In what follows, we will refer to it as volatility of TFPR growth or, more simply, as volatility.

3 Volatility Estimates

The mean standard deviation of the residual across all manufacturing plants is 8.05%. Consistent with analyses that employ alternative methodologies,[9] this result suggests that idiosyncratic risk is substantially larger than aggregate risk.

This can be appreciated by comparing our estimate with readily available measures of aggregate volatility. The average standard deviation of U.S. annual real GDP growth was 2.52% before the so–called great moderation (i.e. in the period 1950–1978) and fell to 1.75% in the period 1979–2007.

[6] In order to treat all plants in the sample symmetrically (whether small or large), we do not use the ASM sample weights As discussed in Davis, Haltiwanger, and Schuh (1996) (Section A.2), samples in the ASM panel are rotated every five years. In order to utilize all panel years, we also include growth rates measured between two different ASM samples, namely for the years 1973-74, 1978-79, 1983-84, 1988-89, and 1993-94. Because only "certainty" plants are continuously observed across different ASM panels, our sample in these years may over-represent relatively large plants.

[7] See Hall (1987) and Evans (1987).

[8] 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.

[9] See Campbell, Lettau, Malkiel, and Xu (2001) and Bachman and Bayer (2011), for example.

A more accurate way of assessing the importance of idiosyncratic risk versus aggregate risk is to compare our estimate with a more comprehensive measure of plant–level uncertainty, which also reflects the portion that may be ascribed to industry–wide and economy–wide factors. Such measure can be calculated by regressing TFPR growth on plant fixed effects alone, and then computing the standard deviation of the residuals.

Carrying out this exercise yields an overall volatility estimate of 9.45%. Our conclusion is that idiosyncratic factors appear to account for about 90% of overall plant–level uncertainty.

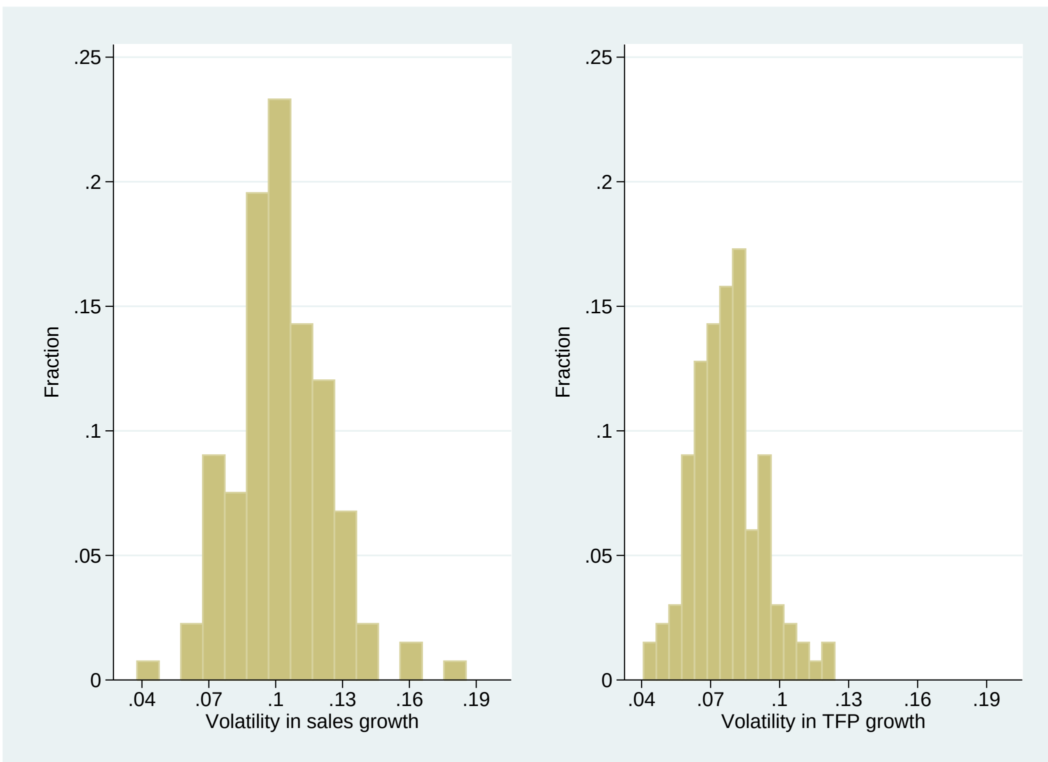

Figure 1: Histogram of idiosyncratic risk by sector.

Our volatility estimates across three–digit industries are reported in Table 5 and illustrated in Figure 1. The height of each bin is the fraction of sectors whose estimated risk falls in the associated interval.

The range of estimates is rather wide. The volatility of TFP growth is lowest in the Fur Goods sector (237), at 4.09%, and highest in Computer Equipment Manufacturing (357), at 12.39%.

3.1 Sales Growth

As a consistency check, we repeated our analysis substituting sales growth for TFPR growth in equation (1). The mean standard deviation of the residuals across all manufacturing plants is 10.07%, larger than above. This is likely to be the case because the scale of production reacts to shocks, no matter their nature, amplifying their impact on sales.

The range of sectoral estimates is also wider than for TFPR. See Table 5. The lowest volatility is attained by Newspaper Publishing (SIC 271), with 3.78%, while the highest pertains to Railroad Equipment (374), with 18.53%. The orderings delivered by the TFPR and sales measures are fairly consistent, but not quite the same. The Spearman's rank–correlation coefficient is 0.71.

Considering sales growth is also interesting because it allows for a direct comparison with the estimates recovered for public companies by Castro, Clementi, and MacDonald (2009). There are two caveats. First and foremost, our data is at the plant–level, while theirs is at the firm level. Secondly, their sector classification is at the three–digit NAICS, which is coarser than ours.

For the sectors for which a match is possible, our estimates are sensibly higher. For Computer and Electronic Product Manufacturing, Castro, Clementi, and MacDonald (2009) report an estimate of 10.52%, lower than the 15.87% we estimate for SIC 357. For Machine Manufacturing, they estimate volatility at 8.89%, a figure lower than our estimates for all sectors producing machinery (SIC 352, 354, 355, 356, and 358). Similarly, their 4.9% estimate for Food Manufacturing is lower than our estimates for the three–digit SIC sectors that belong to that industry (SIC 201 through 207 plus 209).

This pattern is consistent with the findings of Davis, Haltiwanger, Jarmin, and Miranda (2006), who compare the volatility of public Vs. privately held firms, and with the industrial organization literature that documents the negative correlation between growth volatility and size.

3.2 Censoring

Since we do not explicitly account for exit selection, one may wonder whether the cross–sectoral variation in volatility that we uncover were simply the result of censoring. Say that the standard deviation of shocks were the same across industries, but the fixed cost of operation was different. In a standard model of industry dynamics such as Hopenhayn (1992), this would imply heterogeneity in exit thresholds, and therefore cross-sectoral differences in *measured* volatility. The lower the cost, the lower the threshold, and the higher the measured volatility. The same model, however, would imply that sectors with higher measured volatility have lower exit rates.

Using data from the Statistics of US Businesses Database gathered by the US Census Bureau, we computed exit rates across three–digit SIC industries and plotted them against our volatility estimates.[10] See Figure 2. On average, more volatile industries tend to display higher exit rates. This finding suggests that the cross–sectoral

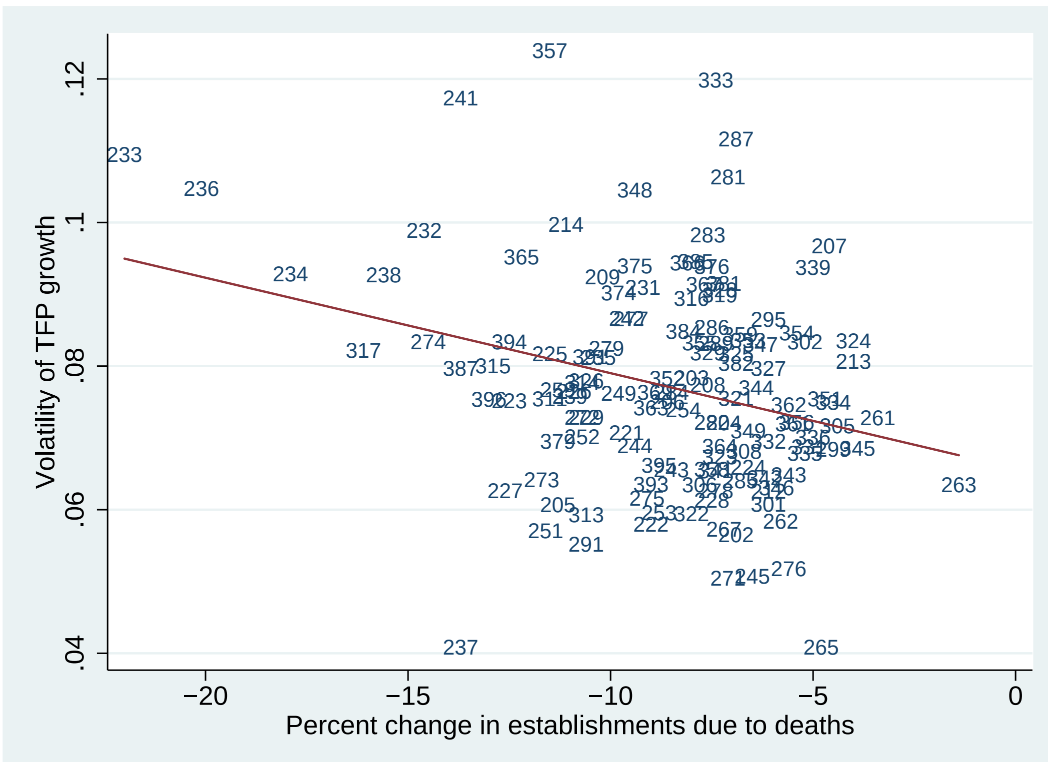

Figure 2: Volatility and Exit Rates.

heterogeneity that we uncover cannot be simply the result of censoring. However, we cannot rule out that censoring indeed biases our estimates, possibly affecting the ranking of sectors by volatility.[11]

One may also wonder to what extent the cross-sectoral heterogeneity in our volatility estimates can be explained by variation in age and size. This question is motivated

[10] Exit rates refer to 1997, the only year in which SUSB and our dataset overlap.

[11] In his study of the ready–mixed concrete industry, Syverson (2004a) finds that markets with denser construction activity have higher lower-bound productivity levels. This heterogeneity has an obvious impact on the measures of productivity dispersion across markets.

by evidence of a systematic relationship between these characteristics and other, alternative measures of plant-level volatility. We refer for example to Davis, Haltiwanger, and Schuh (1996), who document how job reallocation rates decline with both age and size, and to Davis, Haltiwanger, Jarmin, and Miranda (2006), who highlight the negative association between age and the volatility of business growth rates.

In the case of sales growth, however, Castro, Clementi, and MacDonald (2009) find that controlling for age and size in regression (2) has a very limited impact on their volatility estimates.

4 Creative Destruction and Volatility

Why does volatility differ so much across sectors? In this section, we look for evidence in favor of a particular explanation: volatility is higher in sectors where the speed and extent of creative destruction are greater.

Joseph Schumpeter envisioned economic progress as the result of a perpetual race between innovators. Success by a laggard or an outsider in implementing a new process or producing a new good, provides them with a competitive advantage and displaces the previous market leader, eliminating its rent. This, in a nutshell, is the process of creative destruction.

We conjecture that most of the plant–level volatility that we document reflects the turnover between market participants which is at the center of Schumpeter's paradigm. That is, we argue that a large fraction of the fluctuations in a plant's TFPR growth is due to variations in its distance from the technology frontier.

Our strategy consists in looking for sector–specific attributes that are likely to be systematically associated with the speed of turnover. Starting with Aghion and Howitt (1992), Schumpeter's idea was formalized in a large number of models. We turn to this literature for guidance.

In Aghion and Howitt (1992), the producer endowed with the leading technology monopolizes the intermediate good market. Technology improves as a result of purposeful research and development, which in equilibrium is only carried out by prospective entrants. When it succeeds in obtaining a new and more productive variety of intermediate good, the innovator enters and displaces the monopolist. It follows that all the variation in TFPR growth is associated with product turnover.

The positive association between product turnover and plant–level volatility is not specific to Aghion and Howitt (1992). Rather, it is a robust feature of all of its generalizations in which intermediate goods of different vintages are vertically differentiated. For example, see Aghion, Harris, Howitt, and Vickers (2001) and Aghion, Bloom, Bludell, Griffith, and Howitt (2005).

The race can also be among plants that are not directly engaged in R&D, but adopt components which embed innovations made by others. This is the scenario described by Copeland and Shapiro (2010), who model the personal computers industry. The adoption decision, which entails the introduction of a new product, leads to a rise in sales for the adopter, and to a decline for its competitors.

In Samaniego (2009), the decision that yields a competitive advantage is that of acquiring the latest vintage of equipment. The faster is investment–specific technological change, the more frequent is technology adoption by either laggards or new entrants. In turn, this leads to a more frequent turnover in industry leadership and more variability in both sales and TFPR growth.

In the next section, we ask whether product turnover is indeed higher in industries where plants are documented to face a greater volatility of TFPR growth. In Sections 4.2 and 4.3 we will ask whether across sectors our volatility measure is positively related with the intensity of R&D and the speed of investment–specific technological change, respectively.

4.1 Product Turnover

The U.S. Bureau of Labor Statistics collects prices on 70,000–80,000 non–housing goods and services from around 22,000 outlets across various locations. When a product is discontinued, the agency starts collecting prices of a closely related good at the same outlet, and records the substitution information. The BLS classifies goods in narrowly–defined categories known as entry–level items (ELI).

Our proxy for turnover is the average monthly frequency of substitutions, known as the item substitution rate. It is the fraction of goods in the ELI that are replaced on average every month. Our data is drawn from Bils and Klenow (2004)'s tabulations, which in turn are based on information on more than 300 consumer good categories from 1995 to 1997.[12]

Using the algorithm developed by Chang and Hong (2006), we were able to match

[12] The BLS distinguishes between two types of substitutions. Substitutions are comparable when the replacement does not represent a quality improvement over the previous item. They are non-comparable, otherwise. Since average and noncomparable average item substitution rates are highly correlated across good categories, our results did not change much when we used noncomparable item substitution rates instead.

each one of 53 three–digit SIC manufacturing sectors with at least one ELI. For 21 sectors, the correspondence is one–to–one. The remaining 32 are matched to 213 items. In such cases, we defined the substitution rate as the average of the associated ELIs' rates, weighted by their respective CPI weights.

Two caveats are worth mentioning. To start with, the BLS data focuses on consumer goods. Most investment good sectors are missing. Furthermore, the substitution rate only tells about the frequency of product turnover and does not provide information about the *size of the step*, i.e. the extent to which a new product improves over the pre–existing one.

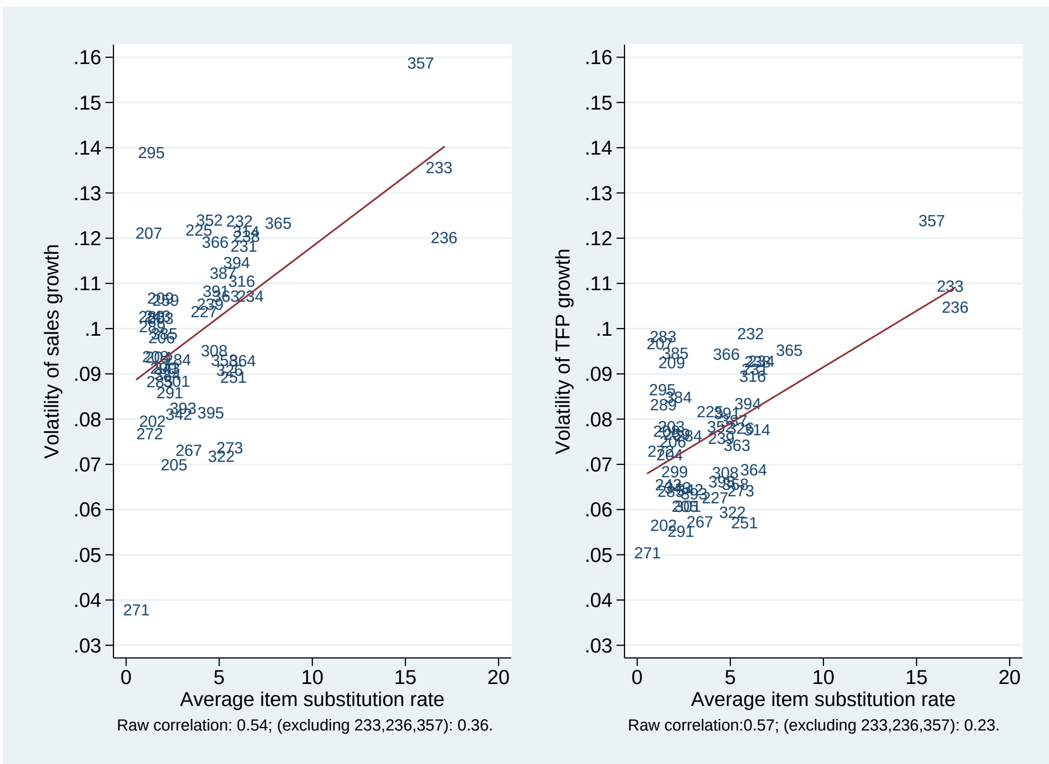

Figure 3: Idiosyncratic Risk and Product Substitution Rate.

The scatter plot in Figure 3 shows that our proxy for product turnover is positively associated with the volatility of TFPR growth. The simple correlation coefficients is 0.571.

Three sectors stand out, as they are characterized by high volatility and remarkably high substitution rates. They are Computer and Office Equipment (357), Women's and Misses' Outerwear (233), and Girls' and Children's Outerwear (236).

Anecdotal evidence as well as scholarly research[13] suggest that SIC 357 epitomizes the idea of creative destruction. However, product turnover in the other two sectors is not likely to be driven by technological improvements.

Idiosyncratic risk and turnover are positively associated even when we exclude SIC 233, 236, and 357. However, the correlation coefficient drops to 0.235.[14]

The last two columns in Table 1 report the results of regressing TFPR growth volatility on the average substitution rate and a constant. Column 3 tells us that on average, a 1% higher substitution rate implies a 0.25% higher volatility of TFPR growth. Without SIC 233, 236, and 357 (see column 4), the coefficient is marginally insignificant at the 10% confidence level (its p–value is 0.101).

Table 1: Idiosyncratic Risk and Product Substitution Rate.

Dependent Variable:	**Sales Growth Volat.**		**TFPR Growth Volat.**	
	(1)	(2)	(3)	(4)
Substitution Rate	0.0031***	0.0034**	0.0025***	0.0016
	(0.0007)	(0.0013)	(0.0005)	(0.0009)
Constant	0.0870***	0.0862***	0.0666***	0.0697***
	(0.0038)	(0.0052)	(0.0028)	(0.0039)
Observations	53	50	53	50
R^2	0.295	0.129	0.326	0.055

Standard errors in parenthesis. ***Significant at 1%. **Significant at 5%. *Significant at 10%.
Specifications in columns (2) and (4) exclude SIC 233, 236, and 357.

Many establishments in the ASM are likely to produce more than one product. Possibly, many more. As long as the correlation between sales from different lines of business is less than 1, plant–level sales growth volatility will be lower than average volatility at the level of product line. This may explain why sectors such as Glass and Glassware (322), Books (273), and Household Furniture (251) are characterized by a relatively high item substitution rate and low volatility of TFPR growth.

4.2 R&D Intensity

Unfortunately we lack data on research and development expenditure in the ASM. We measure a sector's research intensity as the ratio of R&D expenditure to sales in COMPUSTAT. The latest CENSUS–NSF R&D survey found that most of the

[13]See Copeland and Shapiro (2010) and citations therein.

[14]For sales growth volatility, the correlation coefficient is 0.543. Without SIC 233, 236, and 357, it drops to 0.359.

research and development activity takes place at large firms. This leads us to think that the cross–sectoral variation in R&D expenditures in the population is not likely to differ much from that for large, public firms.

The cross–industry variation in research expenditures that we uncover is substantial. Our measure of research intensity varies from 0.022% for Book Binding (SIC 278) to 7.77% for firms in Drugs (283).

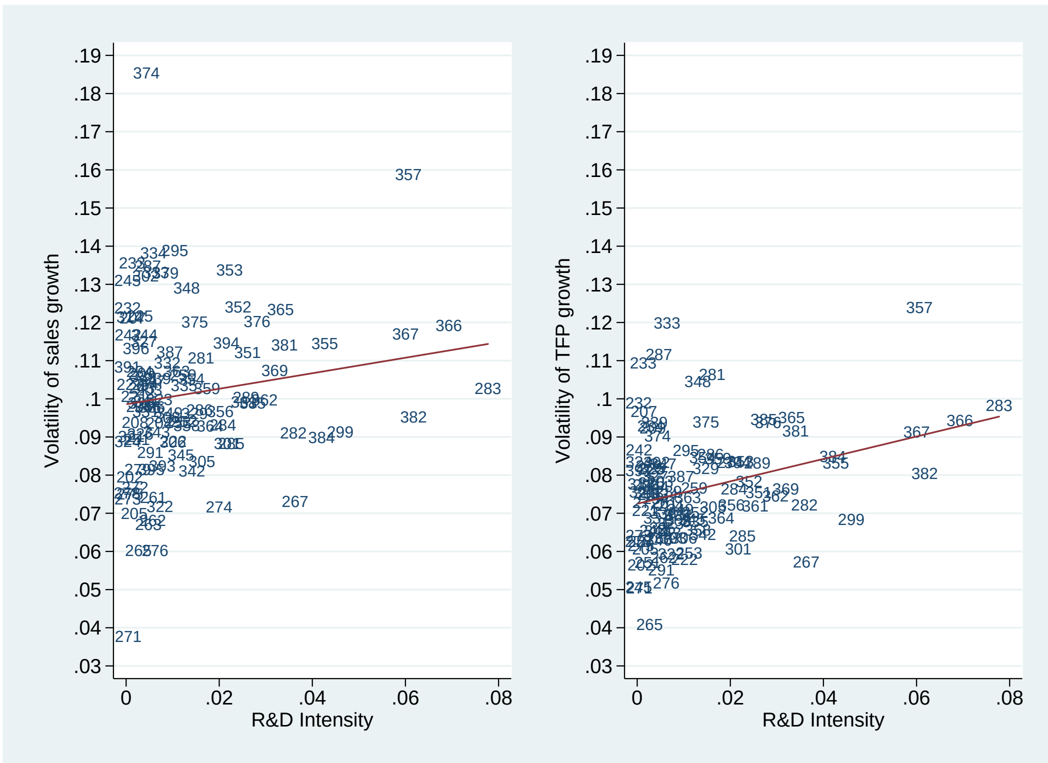

Figure 4: Idiosyncratic Risk and R&D.

The unconditional relationship between our risk proxy and research intensity is illustrated in Figure 4. In Table 2 we report the results of regressing volatility on R&D intensity and a constant. In the case of TFPR, the coefficient of R&D intensity is statistically and economically significant. At the mean, a 1% increase in research intensity implies an increase in volatility of about 30%.

Since Griliches (1979), the relation between R&D and productivity growth has been the object of interest for a large number of studies. The results described above are consistent with recent findings by Doraszelski and Jaumandreu (2011). For a large sample of Spanish manufacturing firms, they establish that engaging in R&D introduces uncertainties in the productivity process that would be absent otherwise.

Table 2: Idiosyncratic Risk and Research Intensity.

Dependent Variable:	**Sales Growth Volat.**	**TFPR Growth Volat.**
R&D Intensity	0.2033	0.2938***
	(0.1292)	(0.0858)
Constant	0.0986***	0.0725***
	(0.0027)	(0.0018)
Observations	109	109
R^2	0.0226	0.0988

Standard errors in parenthesis. ***Significant at 1%. **Significant at 5%. *Significant at 10%.

4.3 Investment–Specific Technological Change

In a simple two–sector model where investment and consumption goods are produced competitively, the quality improvement in the investment good equals the negative of the change in its relative price. Exploiting this restriction, Cummins and Violante (2002) computed time series of quality improvement – or technological change – for a variety or equipment goods over the period 1948–2000.

Using detailed data on capital expenditures by two–digit SIC industries provided by the Bureau of Economic Analysis, Cummins and Violante (2002) also constructed measures of investment–specific technological change by sector. In this section we ask whether such measures are systematically related to our proxies for risk.

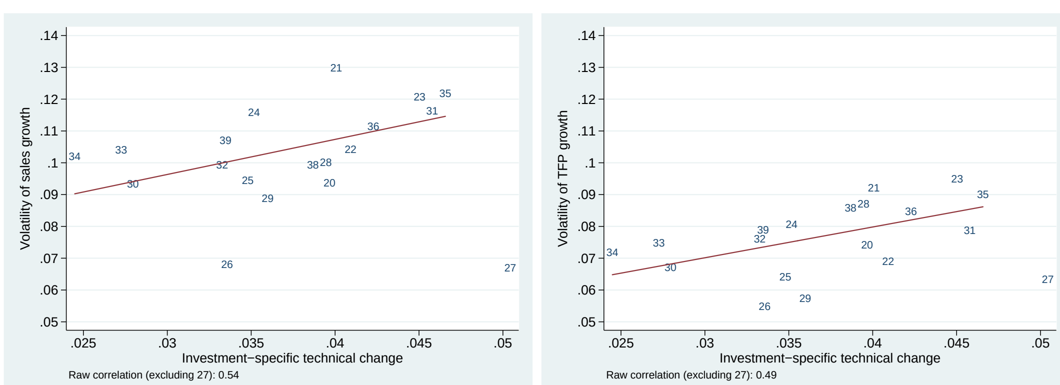

Figure 5: Idiosyncratic Risk and Investment–Specific Technological Change.

Given the level of aggregation in the data on technological change, our analysis is confined to 19 two–digit SIC sectors, listed in Table 6. For each industry, the rate of technological change is the average of the 1948–1999 annual time–series underlying

Figure 2 in Cummins and Violante (2002), provided to us by Gianluca Violante. The risk proxies are weighted averages of the volatility estimates for the three–digit SIC sectors that belong to the industry. The weights are the values of the average share of each three-digit sector's value of shipments in the corresponding two–digit sector.[15]

The scatter plots in Figure 5 suggest a positive association between the two variables of interest. Sectors such as SIC 35 (Industrial and Commercial Machinery and Computer Equipment) and 31 (Leather and Leather Products) display high volatility and high investment–specific technological change. SIC 34 (Fabricated Metal Products, except Machinery and Transportation Equipment), which ranks last in terms of technological change, is also among the least uncertain sectors.

Table 3: Idiosyncratic Risk and Investment–Specific Technological Change.

Dependent Variable:	**Sales Growth Volat.**	**TFP Growth Volat.**
ISTC	1.1235**	0.9370**
	(0.5174)	(0.3767)
Constant	0.0997***	0.0417***
	(0.0627)	(0.0141)
Observations	18	18
R^2	0.228	0.279

Standard errors in parenthesis. ***Significant at 1%. **Significant at 5%. *Significant at 10%.
Note: SIC 27 excluded.

The magnitude and statistical significance of the correlation coefficients depends on an outlier observation, SIC 27 (Printing and Publishing). Given the small number of data–points, this is not surprising. Unfortunately we were not able to make sense of the finding that plants mostly engaged in the printing and publishing of books, periodicals, and newspapers experienced the fastest investment-specific technological progress.

When we exclude SIC 27, the raw correlation between the volatility of TFPR growth and investment–specific technological change is 0.53. Both estimates are significantly different from zero at the 5% confidence level. When we include the outlier, the correlation drops to 0.33, not statistically significant at the 10% level.[16]

Table 3 reports the results of regressing our proxies for idiosyncratic risk on a constant and the estimated speed of investment–specific technological change. When

[15] The averages are computed from the NBER manufacturing database, which covers the 1958-1997 period.

[16] With sales growth, the volatility estimates are 0.58 and 0.13 without and with SIC 27, respectively.

we drop SIC 27, a 1% increase in ISTC is associated with a 0.93% increase in TFPR growth. The estimate is significant at the 5% level.

5 Consumption Vs. Investment Goods

Castro, Clementi, and MacDonald (2009) showed that in COMPUSTAT firms producing investment goods are significantly riskier than firms producing consumption goods. Does this pattern also hold across manufacturing plants in the ASM?

We classify industries as either consumption– or investment good–producing, based on the 1992 BEA's Use Input–Output Matrix. For every sector, the Use Matrix reports the fractions of its output that reach all other sectors as input, as well as the portions that meet final demand uses.

For each three–digit SIC industry, we compute the output share whose ultimate destination is either consumption or investment. We label an industry as "consumption" or "investment" if a sufficiently large share of its production ultimately meets a demand for consumption or investment, respectively. The outcome of our assignment procedure is in Table 5. The details of the algorithm are in Appendix A.2.

Figure 6 suggests a clear tendency for investment good sectors to be among the most volatile, no matter the proxy for risk. The height of each bar reflects the volatility of one three–digit sector.

Computer equipment is the most volatile sector. Only one investment–good sector – Wood Buildings (245) – is among the bottom 28 sectors in the ranking.

Formal tests confirm that on average investment–good producing plants are indeed more volatile. We run the following regression:

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

where α is a constant and θ_C is a dummy variable which takes value 1 if firm i produces consumption goods and is zero otherwise. The average volatility is 8.49% in investment good sectors and 7.62% in consumption good industries. We can reject the hypothesis that the two estimates are equal at the 1% confidence level.[17]

At business–cycle frequencies, the difference in volatility between aggregate consumption and investment expenditures is mostly driven by the difference in durability between the two good categories. In fact, expenditures on durable consumption goods

[17] With sales growth, the mean volatility among investment good–producing plants is 11.18%, while for consumption good–producing plants it is 9.33%. The difference is also statistically significant.

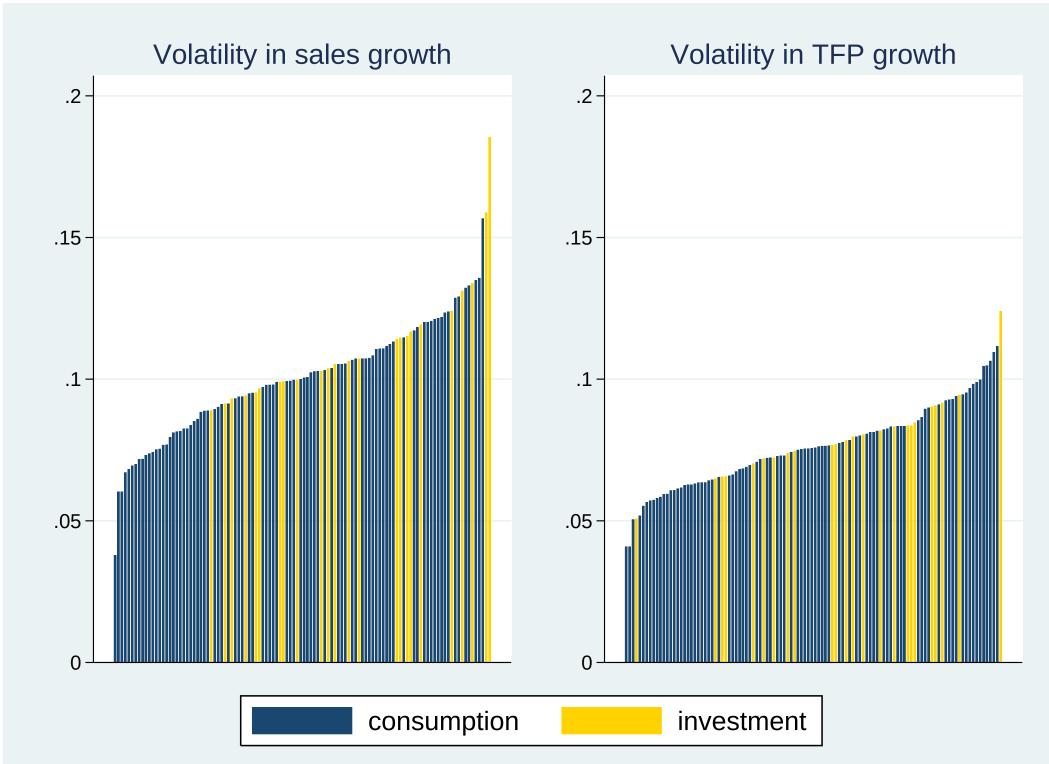

Figure 6: Volatility of sales growth per three–digit industry.

Table 4: Idiosyncratic Risk and Durability

Dependent Variable:	**Sales Growth**	**TFPR Growth**
Non-Durable Cons. Dummy	–0.3963***	–0.1331***
	(0.024)	(0.0242)
Durable Cons. Dummy	–0.1621***	–0.1463***
	(0.0372)	(0.0365)
Constant	–4.3835***	–4.9361***
	(0.0137)	(0.0148)
Observations	446,837	428,888

Standard errors in parenthesis. ***Significant at 1%. **Significant at 5%. *Significant at 10%.

are almost as volatile as investment expenditures. Does a similar pattern emerge at the plant level?

To test whether volatility co–varies systematically with durability, we run the regression

$$\ln \hat{\varepsilon}_{ijt}^{2} = \alpha + \theta_D + \theta_{ND} + u_{ijt}, \tag{4}$$

where θ_D and θ_{ND} are dummy variables that equal 1 if the firm produces durable or non–durable consumption goods, respectively.

We classify consumption goods as durable 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. The regression's results are reported in Table 4.

We find no appreciable difference in TFPR growth volatility between establishments producing durable and non–durable consumption goods.[18]

Estimated risk in sectors producing durable consumption goods is statistically and economically lower than in investment good sectors. The bottom line is that we found no evidence in support of the claim that durability is the reason why investment–good producing plants bear a greater idiosyncratic risk than plants producing consumption goods.

6 Conclusion

In the recent but fast growing theoretical literature on establishment dynamics, heterogeneity in outcomes is often driven by idiosyncratic shocks. This paper makes some progress towards understanding the magnitude and cross–sectoral variation of such disturbances.

Using a large panel representative of the entire US manufacturing sector, we found that idiosyncratic risk accounts for about 90% of the overall uncertainty faced by plants. We also showed that risk varies greatly across three–digit sectors, ranging from 4.09% for producers of fur goods to 12.4% for producers of computer equipment.

We propose that the heterogeneity in idiosyncratic risk is driven by the differential extent to which creative destruction shapes competition across sectors. Formal models of Schumpeterian competition imply a positive correlation between the speed of technological progress, product turnover, and volatility in plant–level outcomes. We provide evidence in support of these predictions. In particular, our proxy for idiosyncratic risk is positively associated with measures of product turnover and investment–specific technological change.

We acknowledge that our evidence is not conclusive. Other factors are likely to contribute to the heterogeneity that we document. Syverson (2004b) outlines a variety

[18] Plants producing nondurable consumption goods have a sales growth volatility of 9.17%, lower than estimated for the consumption sector as a whole.

of sectoral characteristics that may be related to measures of within–sector dispersion in productivity levels. In most models of firm dynamics, many of those characteristics would also impact the dispersion productivity growth rates. For sure, this is the case for the parameters that drive entry and exit.

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 plants 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, $Y_C(j)/\left(Y_C(j) + Y_I(j)\right)$. 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 do not assign a consumption/investment good classification to the remaining industries (these industries do not receive a good classification in the last column of Table 5).

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 do not assign a durable/nondurable consumption classification to three–digit sectors that are not considered in Bils and Klenow (1998) (these sectors with no service life information are labeled as "Other Consumption" in last column of Table 5).

B Tables

Table 5: Volatility Estimates

SIC		TFP Growth	Rank	Sales Growth	Rank	Good Classification
357	Computer Equipment	0.12395	1	0.15876	2	Investment
333	Primary Nonferrous Metals	0.11988	2	0.13311	10	
241	Logging	0.11737	3	0.14143	4	
287	Agricultural Chemicals	0.11162	4	0.13484	8	Other Consumption
233	Women's Outerwear	0.10947	5	0.13566	7	Other Consumption
281	Industrial Inorganic Chems	0.10638	6	0.11076	40	Other Consumption
236	Girls' Outerwear	0.10478	7	0.12010	25	Nondurable Consumption
348	Small Arms & Ammo	0.10458	8	0.12910	14	Durable Consumption
214	Tobacco Stemming	0.09972	9	0.15666	3	Other Consumption
232	Men's Clothing	0.09891	10	0.12381	17	Nondurable Consumption
283	Drugs	0.09825	11	0.10269	65	Nondurable Consumption
207	Fats & Oils	0.09674	12	0.12118	21	Nondurable Consumption
365	Household Audio-Video Eq	0.09520	13	0.12339	18	Durable Consumption
385	Ophthalmic Goods	0.09457	14	0.09895	76	Durable Consumption
366	Communication Equipment	0.09439	15	0.11918	26	Investment
375	Motorcycles, Bicycles	0.09396	16	0.12012	24	Durable Consumption

Table 5: (continued)

SIC		TFP Growth	Rank	Sales Growth	Rank	Good Classification
376	Guided Missiles, Space Vcl	0.09389	17	0.12031	23	
339	Misc Primary Metal Prods	0.09377	18	0.10594	52	
234	Women's Underwear	0.09287	19	0.10716	49	Nondurable Consumption
238	Misc. Apparel	0.09271	20	0.12047	22	Other Consumption
209	Misc. Food	0.09245	21	0.10673	50	Nondurable Consumption
381	Navigation Equipment	0.09154	22	0.11408	35	Investment
367	Elect Components & Acess	0.09137	23	0.11702	29	
231	Men's Suits & Coats	0.09100	24	0.11826	27	Durable Consumption
328	Stone Products	0.09065	25	0.10721	48	Investment
374	Railroad Equipment	0.09023	26	0.18537	1	Investment
319	Other Leather Goods	0.08991	27	0.10306	61	Other Consumption
316	Luggage	0.08945	28	0.11053	42	Durable Consumption
242	Sawmills & Planing Mills	0.08666	29	0.11679	30	
277	Greeting Cards	0.08657	30	0.08253	112	Other Consumption
295	Asphalt Paving & Roofing	0.08653	31	0.13896	5	
286	Organic Chemicals	0.08541	32	0.09712	81	Other Consumption
384	Medical Instr & Supplies	0.08487	33	0.08983	101	
354	Metalworking Machinery	0.08463	34	0.10524	56	Investment
359	Industrial Machinery	0.08442	35	0.10275	63	
353	Construction & Mining	0.08360	36	0.13379	9	Investment
324	Cement, Hydraulic	0.08350	37	0.08890	103	Investment
274	Misc. Publishing	0.08340	38	0.07167	126	Durable Consumption
302	Rubber Footwear	0.08337	39	0.13218	12	Other Consumption
394	Dolls, Toys, & Games	0.08337	40	0.11467	33	Durable Consumption
355	Special Industry Machinery	0.08322	41	0.11449	34	Investment
289	Misc. Chemicals	0.08320	42	0.10044	68	Other Consumption
347	Metal Services	0.08300	43	0.10466	57	
279	Services for Printing	0.08247	44	0.08157	114	Other Consumption
317	Handbags	0.08220	45	0.12864	15	Other Consumption
329	Misc Nonmetal Mineral Prod	0.08183	46	0.09619	75	
325	Clay Products	0.08172	47	0.09898	75	Investment
225	Knitting Mills	0.08169	48	0.12179	19	Nondurable Consumption
391	Jewelry & Silverware	0.08127	49	0.10831	44	Durable Consumption
235	Hats & Caps	0.08120	50	0.10723	47	Other Consumption
213	Chewing Tobacco	0.08065	51	0.07677	118	Nondurable Consumption
382	Measuring Instruments	0.08039	52	0.09520	86	Investment
315	Leather Gloves	0.08004	53	0.10528	54	Other Consumption
387	Watches, Clocks	0.07968	54	0.11230	37	Durable Consumption
327	Concrete & Plaster	0.07967	55	0.11510	32	Investment
203	Canned Fruits & Vegtbls	0.07838	56	0.10232	66	Nondurable Consumption
352	Farm Machinery	0.07832	57	0.12404	16	Investment
326	Pottery & Related Prods	0.07798	58	0.09079	99	
314	Footwear	0.07772	59	0.12151	20	Nondurable Consumption
208	Beverages	0.07738	60	0.09384	91	Nondurable Consumption
344	Metal Products	0.07699	61	0.11675	31	Investment
259	Misc. Furniture	0.07670	62	0.10632	51	Investment
226	Dyeing Textiles	0.07652	63	0.11155	39	Other Consumption

Table 5: (continued)

SIC		TFP Growth	Rank	Sales Growth	Rank	Good Classification
369	Electrical Equipment	0.07637	64	0.10743	45	Other Consumption
284	Detergents & Cosmetics	0.07635	65	0.09316	93	Nondurable Consumption
249	Misc. Wood Products	0.07621	66	0.10526	55	Other Consumption
239	Misc. Textiles	0.07578	67	0.10541	53	Other Consumption
321	Flat Glass	0.07555	68	0.09015	100	Other Consumption
351	Engines & Turbines	0.07548	69	0.11222	38	
311	Leather Finishing	0.07547	70	0.11066	41	Other Consumption
396	Buttons & Needles	0.07537	71	0.11319	36	Other Consumption
223	Wool Fabric	0.07520	72	0.09795	78	Other Consumption
206	Sugar	0.07500	73	0.09798	77	Nondurable Consumption
334	Secondary Nonferrous Mat	0.07495	74	0.13830	6	
362	Electrical Apparatus	0.07462	75	0.09969	70	Investment
363	Households Appliances	0.07423	76	0.10724	46	Durable Consumption
254	Shelving & Lockers	0.07390	77	0.10374	59	Investment
229	Misc. Textile Goods	0.07291	78	0.09926	73	Other Consumption
272	Periodicals: Publishing	0.07291	79	0.07673	119	Nondurable Consumption
261	Pulp Mills	0.07279	80	0.07413	122	Other Consumption
356	General Industry Machinery	0.07220	81	0.09665	83	Investment
282	Plastic Materials	0.07219	82	0.09113	98	Other Consumption
204	Grain Mill Products	0.07213	83	0.09375	92	Nondurable Consumption
361	Electr. Distrib. Equipment	0.07199	84	0.09918	74	Investment
305	Packing Devices	0.07169	85	0.08365	111	Other Consumption
349	Misc Fabricated Metal Prod	0.07097	86	0.09626	84	
221	Cotton Fabric	0.07074	87	0.10063	67	Other Consumption
252	Office Furniture	0.07019	88	0.09415	89	Investment
336	Nonferrous Foundries	0.07006	89	0.09791	79	
379	Misc. Transportation	0.06957	90	0.13299	11	Durable Consumption
332	Iron & Steel Foundries	0.06956	91	0.10944	43	
244	Wood Containers	0.06894	92	0.09968	71	Other Consumption
364	Elec Lighting and Wiring	0.06883	93	0.09294	95	
331	Blast Furnace & Steel Prd	0.06877	94	0.09671	82	
345	Screw Machine Prods, Bolts	0.06857	95	0.08529	109	
299	Misch. Petroleum	0.06841	96	0.09132	96	Nondurable Consumption
308	Misc. Plastic Prods	0.06815	97	0.09511	87	Other Consumption
335	Nonferrous Rolling & Draw	0.06788	98	0.10349	60	
323	Glass Products	0.06740	99	0.09988	69	Other Consumption
395	Pens & Pencils	0.06620	100	0.08148	115	Other Consumption
224	Narrow Fabric	0.06589	101	0.08507	110	Other Consumption
358	Refrigeration Machinery	0.06565	102	0.09309	94	Investment
243	Millwork	0.06554	103	0.10280	62	Investment
341	Metal Cans	0.06542	104	0.09936	72	Other Consumption
343	Heating Equipment	0.06487	105	0.09128	97	Investment
342	Cutlery	0.06443	106	0.08111	116	Other Consumption
273	Books	0.06419	107	0.07374	123	Durable Consumption
285	Paints	0.06403	108	0.08834	107	
393	Musical Instruments	0.06352	109	0.08243	113	Durable Consumption
306	Rubber Products	0.06351	110	0.08877	105	Other Consumption

Table 5: (continued)

SIC		TFP Growth	Rank	Sales Growth	Rank	Good Classification
263	Paperboard Mills	0.06347	111	0.06706	130	Other Consumption
346	Metal Forging	0.06303	112	0.09790	80	Other Consumption
227	Carpets & Rugs	0.06267	113	0.10379	58	Durable Consumption
278	Bookbinding	0.06266	114	0.07535	120	Other Consumption
212	Cigars	0.06254	115	0.09491	88	Nondurable Consumption
275	Commercial Printing	0.06162	116	0.07514	121	Other Consumption
228	Yarn & Thread Mills	0.06134	117	0.10274	64	Other Consumption
301	Tires	0.06074	118	0.08837	106	Nondurable Consumption
205	Bakery Products	0.06070	119	0.06991	127	Nondurable Consumption
253	Public Bldg Furniture	0.05956	120	0.09389	90	
322	Glass & Glasware	0.05942	121	0.07177	125	Durable Consumption
313	Shoe Cut Stock	0.05930	122	0.11712	28	Other Consumption
262	Paper Mills	0.05839	123	0.06812	129	Other Consumption
222	Silk Fabric	0.05795	124	0.08886	104	Other Consumption
267	Converted Paper Prods	0.05732	125	0.07314	124	Other Consumption
251	Household Furniture	0.05710	126	0.08932	102	Durable Consumption
202	Dairy Products	0.05650	127	0.07950	117	Nondurable Consumption
291	Petroleum Refining	0.05521	128	0.08590	108	Nondurable Consumption
276	Business Forms	0.05176	129	0.06022	132	Other Consumption
245	Wood Buildings	0.05076	130	0.13110	13	Investment
271	Newspapers: Publishing	0.05047	131	0.03780	133	Nondurable Consumption
265	Paperboard Containers	0.04087	132	0.06024	131	Other Consumption
237	Fur Goods	0.04087	133	0.06940	128	Other Consumption

Table 6: 1987 SIC

SIC	Description
20	Food and Kindred Products
21	Tobacco Products
22	Textile Mill Products
23	Apparel
24	Lumber and Wood Products
25	Furniture
26	Paper Products
27	Printing and Publishing
28	Chemicals
29	Petroleum Refining
30	Rubber and Miscellaneous Plastics Products
31	Leather and Leather Products
32	Stone, Clay, Glass, and Concrete Products
33	Primary Metal Industries
34	Fabricated Metal Products, except Machinery and Transportation Equipment
35	Industrial and Commercial Machinery and Computer Equipment
36	Electronic and Other Electrical Equipment, except Computer Equipment
38	Instruments and Related Products
39	Miscellaneous Manufacturing Industries

References

Abraham, A., and K. White (2006): "The Dynamics of Plant–Level Productivity in US Manufacturing," Census Bureau Working Paper #06-20.

Aghion, P., N. Bloom, R. Bludell, R. Griffith, and P. Howitt (2005): "Competition and Innovation: An Inverted-U Relationship," *Quarterly Journal of Economics*, 120(2), 701–728.

Aghion, P., C. Harris, P. Howitt, and J. Vickers (2001): "Competition, Imitation, and Growth with Step–by–Step Innovation," *Review of Economic Studies*, 68, 467–492.

Aghion, P., and P. Howitt (1992): "A Model of Growth through Creative Destruction," *Econometrica*, 60, 323–51.

Bachman, R., and C. Bayer (2011): "Investment Dispersion and The Business Cycle," University of Michigan.

Baily, M. N., E. J. Bartelsman, and J. Haltiwanger (2001): "Labor Productivity: Structural Change And Cyclical Dynamics," *The Review of Economics and Statistics*, 83(3), 420–433.

Baily, M. N., C. Hulten, and D. Campbell (1992): "Productivity Dynamics in Manufacturing Plants," *Brooking Papers on Economic Activity: Microeconomics*, 4(1), 187–267.

Bartelsman, E., and P. Dhrymes (1998): "Productivity Dynamics: US Manufacturing Plants, 1972–1986," *Journal of Productivity Analysis*, 9, 5–34.

Bartelsman, E., and M. Doms (2000): "Understanding Productivity: Lessons from Longitudinal Microdata," *Journal of Economic Literature*, 38, 569–594.

Bartelsman, E. J., and W. Gray (1996): "The NBER Manufacturing Productivity Database," NBER Technical Working Papers 0205, National Bureau of Economic Research, Inc.

Bils, M., and Y. Chang (2000): "Understanding how price responds to costs and production," *Carnegie-Rochester Conference Series on Public Policy*, 52(1), 33–77.

Bils, M., and P. J. Klenow (1998): "Using Consumer Theory to Test Competing Business Cycle Models," *Journal of Political Economy*, 106(2), 233–261.

——— (2004): "Some Evidence on the Importance of Sticky Prices," *Journal of Political Economy*, 112(5), 947–985.

Caggese, A. (2012): "Entrepreneurial Risk, Investment and Innovation," *Journal of Financial Economics*, Forthcoming.

Campbell, J. Y., M. Lettau, B. G. Malkiel, and Y. Xu (2001): "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk," *Journal of Finance*, 56(1), 1–43.

Castro, R., G. L. Clementi, and G. MacDonald (2004): "Investor Protection, Optimal Incentives, and Economic Growth," *Quarterly Journal of Economics*, 119(3), 1131–1175.

——— (2009): "Legal Institutions, Sectoral Heterogeneity, and Economic Development," *Review of Economic Studies*, 76(2), 529–561.

Chang, Y., and J. Hong (2006): "Do Technological Improvements in the Manufacturing Sector Raise or Lower Employment?," *American Economic Review*, 96(1), 252–368.

Chun, H., J.-W. Kim, R. Mork, and B. Yeung (2008): "Creative Destruction and Firm–Specific Performance Heteroeneity," *Journal of Financial Economics*, 89, 109–135.

Clementi, G. L., and T. Cooley (2009): "Executive Compensation: Facts," NBER Working Paper # 15426.

Clementi, G. L., and H. A. Hopenhayn (2006): "A Theory of Financing Constraints and Firm Dynamics," *The Quarterly Journal of Economics*, 121(1), 229–265.

Comin, D., and T. Philippon (2005): "The Rise in Firm-Level Volatility: Causes and Consequences," *NBER Macroeconomics Annual*, 20.

Copeland, A., and A. Shapiro (2010): "The Impact of Competition on Technology Adoption: An Apples-to-PCs Analsyis," Federal Reserve Bank of New York.

Cuñat, A., and M. J. Melitz (2010): "Volatility, Labor Market Flexibility, and the Pattern of Comparative Advantage," *Journal of the European Economic Association*, forthcoming.

Cummins, J. G., and G. L. Violante (2002): "Investment-Specific Technical Change in the United States (1947-2000): Measurement and Macroeconomic Consequences," *Review of Economic Dynamics*, 5(2), 243–284.

Davis, S., J. Haltiwanger, and S. Schuh (1996): *Job Creation and Job Destruction*. MIT Press, Cambridge, MA.

Davis, S. J., and J. Haltiwanger (1992): "Gross Job Creation, Gross Job Destruction, and Employment Reallocation," *Quarterly Journal of Economics*, 107(3), 819–863.

Davis, S. J., J. Haltiwanger, R. Jarmin, and J. Miranda (2006): "Volatility and Dispersion in Business Growth Rates: Publicly Traded versus Privately Held Firms," *NBER Macroeconomics Annual*, 21, 107–156.

Doraszelski, U., and J. Jaumandreu (2011): "R&D and Productivity: Estimating Endogenous Productivity," Working Paper, University of Pennsylvania.

Dunne, T., J. Haltiwanger, and K. R. Troske (1997): "Technology and jobs: secular changes and cyclical dynamics," *Carnegie-Rochester Conference Series on Public Policy*, 46(1), 107–178.

Ericson, R., and A. Pakes (1995): "Markov–Perfect Industry Dynamics: A Framework for Empirical Work," *Review of Economic Studies*, 62, 53–82.

Evans, D. (1987): "The Relationship between Firm Growth, Size and Age: Estimates for 100 Manufacturing Firms," *Journal of Industrial Economics*, 35, 567–81.

Foster, L., J. Haltiwanger, and C. Krizan (2001): "Aggregate Productivity Growth: Lessons from Microeconomic Evidence," in *New Developments in Productivity Analysis*, ed. by C. R. Hulten, E. R. Dean, and M. J. Harper, pp. 303–363. University of Chicago Press.

Foster, L., J. Haltiwanger, and C. Syverson (2008): "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?," *American Economic Review*, 98(1), 394–425.

Gourio, F. (2008): "Estimating Firm–Level Risk," Boston University.

Grilliches, Z. (1979): "Issues in assessing the contribution of R&D to productivity growth," *Bell Journal of Economics*, 10(1), 92–116.

Hall, B. (1987): "The Relationship between Firm Size and Firm Growth in the US Manufacturing Sector," *Journal of Industrial Economics*, 35, 583–606.

Herranz, N., S. Krasa, and A. P. Villamil (2009): "Small Firms in the SSBF," *Annals of Finance*, 5, 341–359.

Hopenhayn, H. A. (1992): "Entry, Exit and Firm Dynamics in Long Run Equilibrium," *Econometrica*, 60, 1127–50.

Michelacci, C., and F. Schivardi (2012): "Does Idiosyncratic Business Risk Matter For Growth?," *Journal of the European Economic Association*, Forthcoming.

Quadrini, V. (1999): "Entrepreneurship, Saving, and Social Mobility," *Review of Economic Dynamics*, 3(1), 1–40.

——— (2003): "Investment and Liquidation in Renegotian–Proof Contracts with Moral Hazard," *Journal of Monetary Economics*, 51, 713–751.

Samaniego, R. (2009): "Entry, Exit and Investment–Specific Technical Change," *American Economic Review*, 100(1), 164–192.

Syverson, C. (2004a): "Market Structure and Productivity: A Concrete Example," *Journal of Political Economy*, 112(6), 1181–1222.

——— (2004b): "Product Substitutability and Productivity Dispersion," *Review of Economics and Statistics*, 86(2), 534–550.

——— (2011): "What Determines Productivity?," *Journal of Economic Literature*, 49(2), 326–365.