# Cross–Sectoral Variation in The Volatility of Plant–Level Idiosyncratic Shocks*

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**Abstract**

We estimate the volatility of plant–level idiosyncratic shocks in the U.S. manufacturing sector. Our measure of volatility is the variation in Revenue Total Factor Productivity which is not explained by either industry– or economy–wide factors, or by establishments' characteristics. Consistent with previous studies, we find that idiosyncratic shocks are much larger than aggregate random disturbances, accounting for about 80% of the overall uncertainty faced by plants. The extent of cross–sectoral variation in the volatility of shocks is remarkable. Plants in the most volatile sector are subject to about six times as much idiosyncratic uncertainty as plants in the least volatile. We provide evidence suggesting that idiosyncratic risk is higher in industries where the extent of creative destruction is likely to be greater.

**Key words:** Schumpeterian Competition, Creative Destruction, Product Turnover, R&D Intensity, Investment–Specific Technological Change.

JEL Codes: D24, L16, L60, O30, O31.

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# 1 Introduction

In this study we assess the cross–sectoral variation in the volatility of plant–level idiosyncratic shocks 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.

Our measure of volatility is the variation in 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. Variation in TFPR reflects changes in technical efficiency, as well as shifts in input supply and product demand schedules affecting input and product prices, respectively. We strive to isolate the portion of such variation which is due to plant–specific, random disturbances – a measure of idiosyncratic uncertainty, or risk.

Consistent with previous studies, we find that across the manufacturing sector idiosyncratic uncertainty accounts for the majority – about 80% – of overall plant–level uncertainty. The variation in idiosyncratic risk across 3–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 6.7% for producers of leather soles to a whopping 35.2% for manufacturers of non–ferrous metals.

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.

Our study of the statistical properties of TFPR is of central relevance to most modern models of business dynamics, where TFPR is the most important, if not the only driver of establishment growth and survival. See for example the seminal work of Ericson and Pakes (1995) and Hopenhayn (1992), as well as the more recent

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

information–based theories of Quadrini (2003) and Clementi and Hopenhayn (2006). Establishment growth is driven by improvement in technical efficiency, increases in mark–ups, and declines in input prices. Changes of the opposite sign lead plants to shrink and, eventually, exit.

Learning about the volatility of the innovation to productivity is important in light of the rather general result that, everything else equal, higher volatility implies greater reallocation of inputs across plants and greater plant turnover. Over the last 25 years or so, a large number of cross–sectional studies have 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.

A related body of work, closer to ours in spirit, studies the extent of cross–plant variation in the *growth* of productivity. Davis and Haltiwanger (1992) and Davis, Haltiwanger, and Schuh (1996) document the extent of within–sector job reallocation across manufacturing plants, while Davis, Haltiwanger, Jarmin, and Miranda (2006) describe the time 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 TFPR growth that is due to merely idiosyncratic shocks.

The logarithm of TFPR is modeled as a linear function of its lagged value, size, age, a sector–time dummy variable that accounts for aggregate and industry–wide disturbances, and an establishment–level dummy that stands in for plant unobserved characteristics systematically associated with productivity dynamics. We regard the residuals of this regressions as realizations of random shocks, and their standard deviation as our measure of idiosyncratic risk.

Furthermore, we illustrate the cross–sectoral variation in plant–level idiosyncratic shocks. We provide estimates of risk by 3–digit SIC sectors and make a first attempt at identifying the determinants of the heterogeneity we uncover. As a by–product, our exercise also produces estimates for the sector–specific auto–correlation coefficients of TFPR.

Given that firms' stakeholders have often limited insurance opportunities, assessing establishment–level idiosyncratic risk is relevant for the analysis of scenarios where risk aversion matters. This is the case of entrepreneurship studies such as Michelacci and Schivardi (2013), where idiosyncratic uncertainty hinders business creation via its negative effect on the value of starting new ventures. In information–based theories of economic development such as Castro, Clementi, and MacDonald (2004, 2009), greater idiosyncratic risk is associated with lower capital accumulation via its negative effect on entrepreneurs' ability to secure external finance for their investment projects. Finally, idiosyncratic uncertainty is often cited among the factors restraining innovative activity. See for example 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[2] 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[3] 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 important because the cross–sectoral heterogeneity in risk, when interacted with other features of the economic environment, often generates restrictions on the data that are key to refute economic models. Castro, Clementi, and MacDonald (2009) propose a multi–sector model where incomplete risk–sharing induces cross–sectoral differences in the return on investment in favor of lower–risk sectors. According to their theory, the differences are larger, the poorer is risk–sharing. It turns out that, as long as sectors producing investment goods are riskier than those producing consumption goods, their model has a chance at rationalizing well–established evidence on the cross–country variation of investment rate and the relative price of capital goods. This is a clear case in which model falsification relies on the knowledge of the cross–sectoral variation in volatility.

In Cuñat and Melitz (2010), labor market regulations result in greater inefficiencies in sectors with greater idiosyncratic uncertainty. A testable implications is that countries featuring lower institutional rigidity should specialize in higher–volatility sectors. Once again, knowledge of the cross–sectoral variation of idiosyncratic risk is needed in order to falsify their theory.

[2]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.

[3]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.

Three other papers, by Abraham and White (2006), Gourio (2008), and Bachman and Bayer (2013), 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 on the emphasis we place on the cross–sectoral heterogeneity.[4]

We are not 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).[5] 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.

The remainder of the paper is organized as follows. The data and methodology are described in Section 2. Our volatility estimates across 3–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, and our analysis is carried out at the 3–digit SIC sectoral level, which maps into 4– and 5–digit NAICS. Depending on the year, our data comprises from 50,000 to 70,000 establishments, distributed among

[4] 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.

[5] In the cross–country study by Michelacci and Schivardi (2013), the proxy for risk is built following the methodology of Campbell, Lettau, Malkiel, and Xu (2001).

140 3–digit SIC manufacturing industries.

The ASM allows us (i) to compute reliable estimates of plants' capital stocks, which are needed to compute TFP indicators and, being a panel rather than a cross–section, (ii) to use fixed effects to control for unobserved plant characteristics.

The main drawback is that our data is limited to manufacturing. 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 known in the literature as real revenue per unit input, or Revenue Total Factor Productivity (TFPR). Following Foster, Haltiwanger, and Krizan (2001), Baily, Hulten, and Campbell (1992), and Syverson (2004a) among others, the (log) TFPR for plant $i$ in 3–digit sector $j$ at time $t$ is

$$\ln z_{ijt} \equiv \ln y_{ijt} - \alpha^k_{\iota t} \ln k_{ijt} - \alpha^\ell_{\iota t} \ln \ell_{ijt} - \alpha^m_{\iota t} \ln m_{ijt}, \qquad (1)$$

where $y_{ijt}$ is real sales, $k_{ijt}$ is capital, $\ell_{ijt}$ is labor, and $m_{ijt}$ is materials. Real sales are the nominal value of shipments, deflated using the 4—digit industry–specific deflator from the NBER manufacturing productivity database. The details about the estimation of the residuals in (1) are relegated to Appendix A.2.

The input elasticities are allowed to vary both over time and within 3–digit industries – the index $\iota$ denotes the plant's 4–digit SIC code. This is important for our results in Section 4, as it severely limits the concern that sectors characterized by greater creative destruction display higher volatility in the residuals simply because they are also characterized by greater *unmodeled* time and cross–plant variation in the elasticities.

As effectively pointed out by Foster, Haltiwanger, and Syverson (2008), changes in the TFPR indicator reflect fluctuations in productive efficiency, as well as shifts in product demand and input supply schedules leading to updates in input and output prices. This definition is well suited for our study, as we are interested in identifying all sources of idiosyncratic uncertainty. Our objective is to estimate the volatility of those innovations to TFPR that i) are plant–specific and ii) are not systematically related to observable or unobservable plant characteristics.

We model TFPR as

$$\ln z_{ijt} = \rho_j \ln z_{ij,t-1} + \mu_i + \delta_{jt} + \beta_j \ln(size)_{ijt} + \sum_{s=1}^{3} \psi_{js} D_{ijts} + \varepsilon_{ijt}. \qquad (2)$$

The dummy variable $\mu_i$ is a plant–specific fixed effect that accounts for unobserved persistent heterogeneity across plants. The variable $\delta_{jt}$ denotes a full set of sector–specific year dummies, which control for sector–wide shocks and cross–sectoral differences in business cycle volatility. Size is measured by the number of employees. With $D_{ijts}$ we denote three categories of age dummies: Young, Middle–Aged, and Mature. We include size and age because both were shown to be negatively correlated with plant growth.[6]

The objects of interest are the estimated residuals $\hat{\varepsilon}_{ijt}$, which we will interpret as realizations of plant–specific shocks. An obvious caveat is that the residuals may also reflect measurement error and predictable changes in TFPR not accounted for in (2). This must be kept in mind when considering the magnitude of the volatility estimates reported below.

Recall that our main goal is to charactere 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

$$\ln \hat{\varepsilon}_{ijt}^2 = \theta_j + v_{ijt}, \tag{3}$$

where $\theta_j$ is a sector–specific dummy variable. Letting $\hat{\theta}_j$ denote its point estimate, our measure of the conditional standard deviation of TFPR growth for plants in sector $j$ is $\sqrt{\hat{\gamma}\exp(\hat{\theta}_j)}$, where $\hat{\gamma}$ is our estimate of the mean of the random variable $\exp(v_{ijt})$.[7] In what follows, we will refer to it as volatility of TFPR growth or as idiosyncratic risk.

## 3 Volatility Estimates

Our measure of idiosyncratic uncertainty across all manufacturing plants – obtained by estimating (3) without sector dummies – is 20.53%. This figure is very close to what implied by the findings of Foster, Haltiwanger, and Syverson (2008), and only slightly higher than the value reported by Abraham and White (2006), 16.5%. Most likely, this difference is accounted for by Abraham and White (2006)'s decision to restrict attention to plants with more than 15 observations, decision that biases their sample towards older and possibly less volatile establishments.

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

[7]If $v_{ijt}$ were normally distributed, a consistent estimator of $E[\exp(v_{ijt})]$ would be $\exp(\hat{\sigma}^2/2)$, where $\hat{\sigma}^2$ is the variance of the residuals in (3). Since the normality assumption is easily rejected, we estimated $\hat{\gamma}$ by regressing the squared residuals on the exp of the fitted values generated by (3), without a constant.

We gauge the importance of idiosyncratic risk versus aggregate risk by computing 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 is obtained by means of the methodology introduced in the previous section, amended to exclude the sector–year dummies $\delta_{jt}$ from the specification of (2).

Our point estimate for overall volatility is 26.16%. It follows that idiosyncratic factors appear to account for about 80% of overall plant–level uncertainty. Consistent with studies employing alternative methodologies, such as Campbell, Lettau, Malkiel, and Xu (2001) and Bachman and Bayer (2013), we find that idiosyncratic risk is substantially larger than aggregate risk.

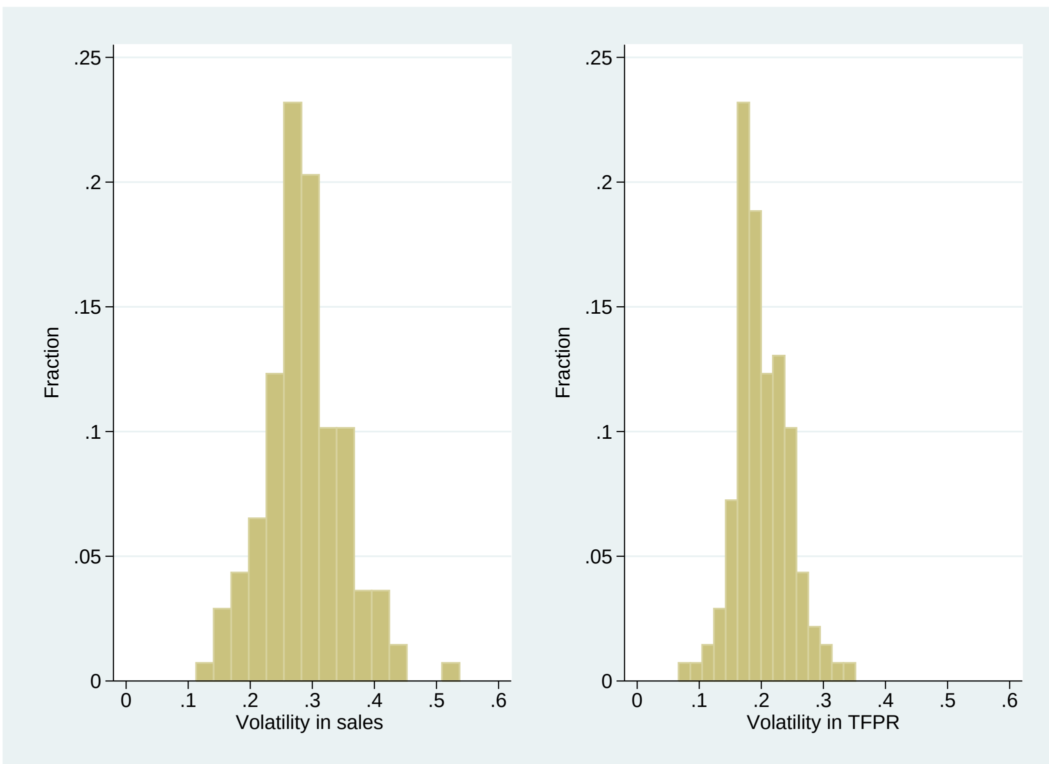


Figure 1: Histogram of idiosyncratic risk by sector.

Our volatility estimates across 3–digit industries are reported in Table 5 and illustrated in the right panel of Figure 1, where sectors are sorted by the magnitude of TFPR volatility. 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 is lowest for Boot and Shoe Cut Stock (SIC 313), at 6.7%, and highest in Primary Smelting and Refining of

Nonferrous Metals (357), at 35.2%.

As a by–product, our exercise also produces estimates for the sector–specific auto–correlation coefficients of TFPR. Our values, reported in Table 5 and illustrated in the right panel of Figure 2, can serve as guidance for the quantitative studies of industry dynamics that model plant–level TFPR as a serially correlated stochastic process. See for example Clementi and Palazzo (2013), Lee and Mukoyama (2009), and Khan and Thomas (2008). The simple arithmetic means of the coefficients is 0.439, a value very close to what reported by Abraham and White (2006).[8]

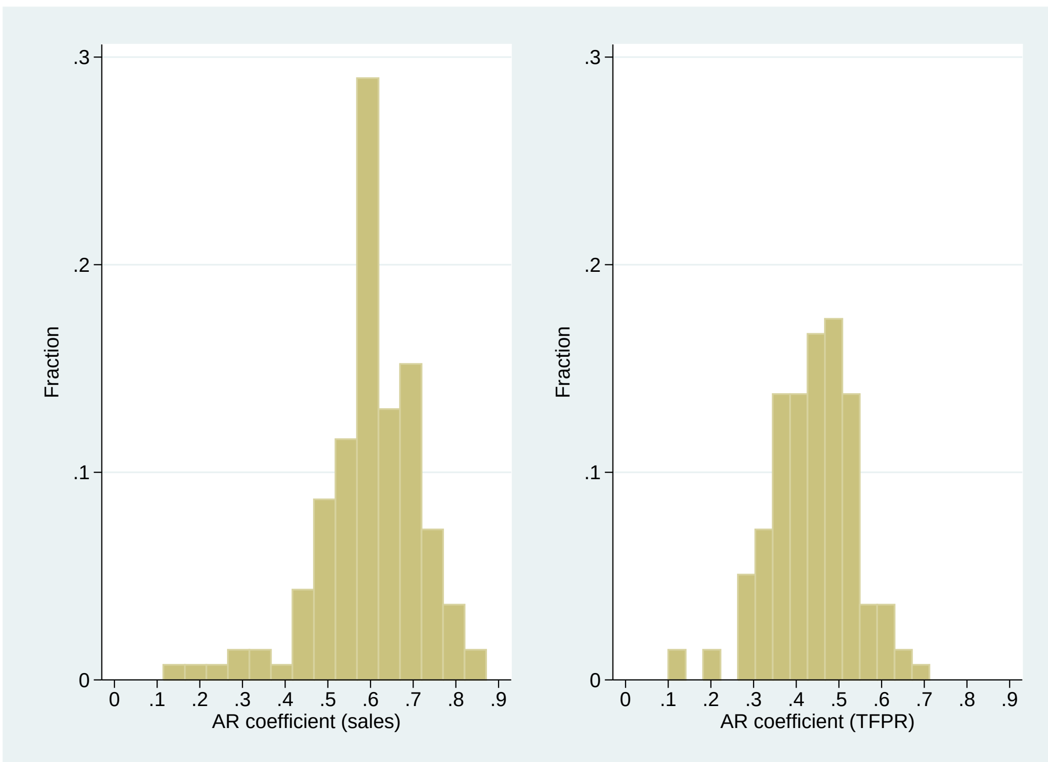


Figure 2: Histogram of autocorrelation coefficients by sector.

### 3.1 Sales

For the purpose of comparison with the rather large literature focusing on sales growth,[9] we repeated our analysis substituting sales for TFPR in equation (2). The mean standard deviation of the residuals across all manufacturing plants is 29.51%,

[8]When we weigh sectors by the value of shipments, the mean autocorrelation drops slightly, to 0.431.

[9]See for example Davis, Haltiwanger, Jarmin, and Miranda (2006).

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 also attained in the Boot and Shoe Cut Stock sector (313), with 11.3%, while the highest pertains to Railroad Equipment (374), with 53.7%. The orderings delivered by the TFPR and sales measures are fairly consistent, but not quite the same. The Spearman's rank–correlation coefficient is 0.66.

### 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 plants in different sectors were burdened by different fixed costs of operation. In most models of industry dynamics, the selection induced by such heterogeneity would generate cross–sectoral difference in measured volatility.

To assess the likelihood that the cross–sectoral variation we uncover is indeed the result of differences in cost structure, consider the model introduced by Hopenhayn (1992). In that framework, under very general conditions, sectors characterized by higher fixed costs will feature higher exit thresholds (in TFPR space) and lower *measured* volatility, but also higher exit rates.

Using data from the Statistics of US Businesses Database gathered by the US Census Bureau, we computed exit rates across 3–digit SIC industries and plotted them against our volatility estimates.[10] See Figure 3. On average, more volatile industries tend to display higher exit rates. This finding suggests that the cross–sectoral 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]

## 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.

[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.

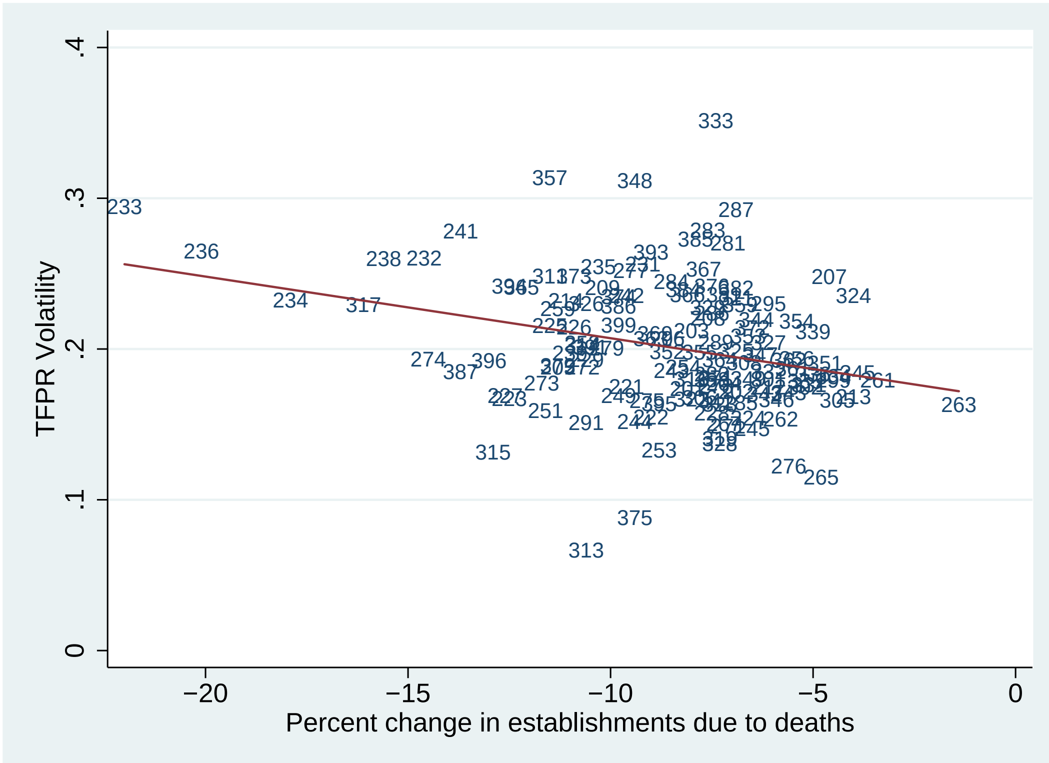


Figure 3: Volatility and Exit Rates.

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.[12]

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 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 technol-

[12] According to this definition of creative destruction, the elimination of its rent will lead the previous leader to exit from a specific product market, but not necessarily to cease operations.

ogy 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 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 (2013), 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.[13]

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. 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.

It should be clear that our methodology cannot establish causality. Our – more limited – goal is to establish whether simple unconditional correlations are consistent with our conjecture on the origin of the cross–sectoral variation in volatility that we uncover.

### 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

[13] Obviously R&D and investment-specific technical change may be – most likely are – vertically related. This is the case because an innovation generated by R&D may turn profitable only when embodied in new capital. See Lach and Rob (1996).

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.[14]

Using the algorithm developed by Chang and Hong (2006), we were able to match each one of 59 3–digit SIC manufacturing sectors with at least one ELI. For 21 sectors, the correspondence is one–to–one. The remaining 38 are matched to several among 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.

The scatter plot in Figure 4 shows that our proxy for product turnover is positively associated with TFPR volatility. The sample correlation coefficient is 0.43.

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[15] 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 0.08.[16]

The last two columns in Table 1 report the results of regressing TFPR volatility on the average substitution rate and a constant. Column 3 tells us that on average,

[14] 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 non–comparable item substitution rates instead.

[15] See Copeland and Shapiro (2013) and citations therein.

[16] For sales volatility, the correlation coefficient is 0.45. Without SIC 233, 236, and 357, it drops to 0.32.

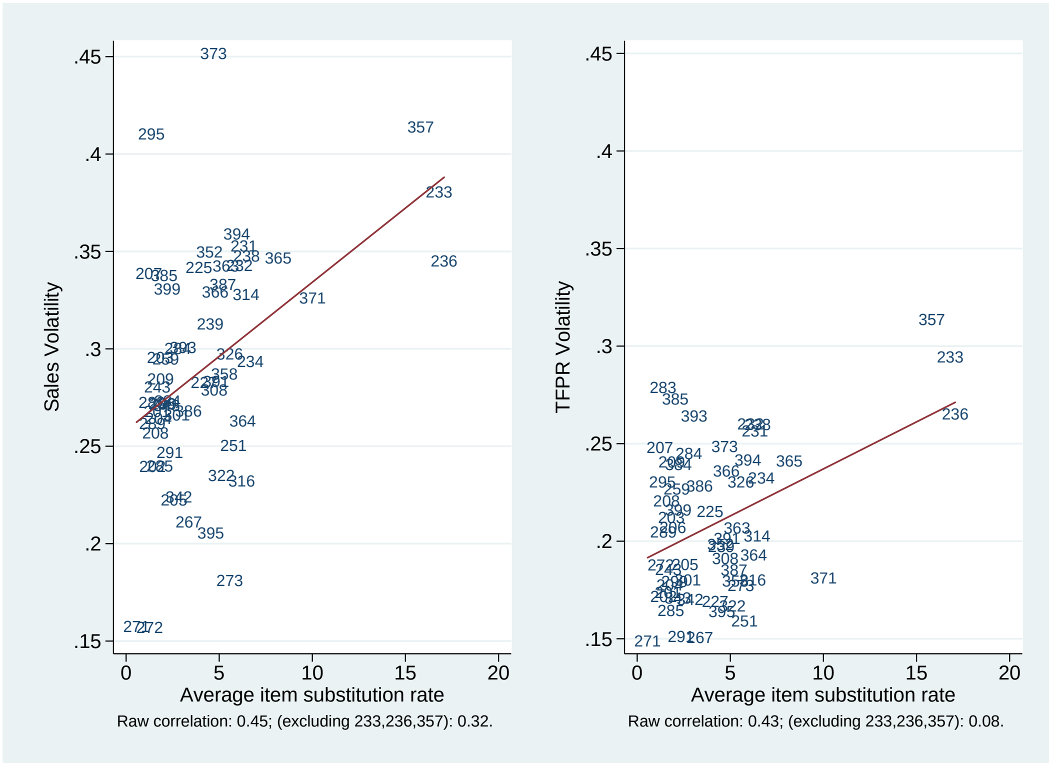


Figure 4: Idiosyncratic Risk and Product Substitution Rate.

a 1 percentage point higher substitution rate implies a 0.48 percentage point higher TFPR volatility. Without SIC 233, 236, and 357 (see column 4), the coefficient becomes insignificant.[17]

Some 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 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.

## 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

[17] Our standard errors of this and the following sections have been computed by a bootstrap procedure aimed at addressing the generated regressor problem.

Table 1: Idiosyncratic Risk and Product Substitution Rate.

| **Dependent Variable:** | **Sales Volatility** | | **TFPR Volatility** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Substitution Rate | $0.0076^{***}$ | $0.0085^{**}$ | $0.0048^{***}$ | 0.0013 |
| | (0.0022) | (0.0037) | (0.0018) | (0.0025) |
| Constant | $0.2581^{***}$ | $0.2549^{***}$ | $0.1889^{***}$ | $0.2008^{***}$ |
| | (0.0123) | (0.0157) | (0.0091) | (0.0106) |
| Observations | 58 | 55 | 58 | 55 |
| $R^2$ | 0.2060 | 0.1003 | 0.1877 | 0.0062 |

Bootstrap 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.

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).

The unconditional relationship between our risk proxy and research intensity is illustrated in Figure 5. 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

Table 2: Idiosyncratic Risk and Research Intensity.

| **Dependent Variable:** | **Sales Volatility** | **TFPR Volatility** |
|---|---|---|
| R&D Intensity | 0.4359 | $0.7509^{***}$ |
| | (0.3467) | (0.2246) |
| Constant | $0.2832^{***}$ | $0.1918^{***}$ |
| | (0.0084) | (0.0055) |
| Observations | 115 | 115 |
| $R^2$ | 0.0129 | 0.0865 |

Bootstrap standard errors in parenthesis.

$^{***}$Significant at 1%. $^{**}$Significant at 5%. $^{*}$Significant at 10%.

is statistically and economically significant. A 1 percentage point increase in research intensity implies an increase in volatility of about 0.75 percentage points.

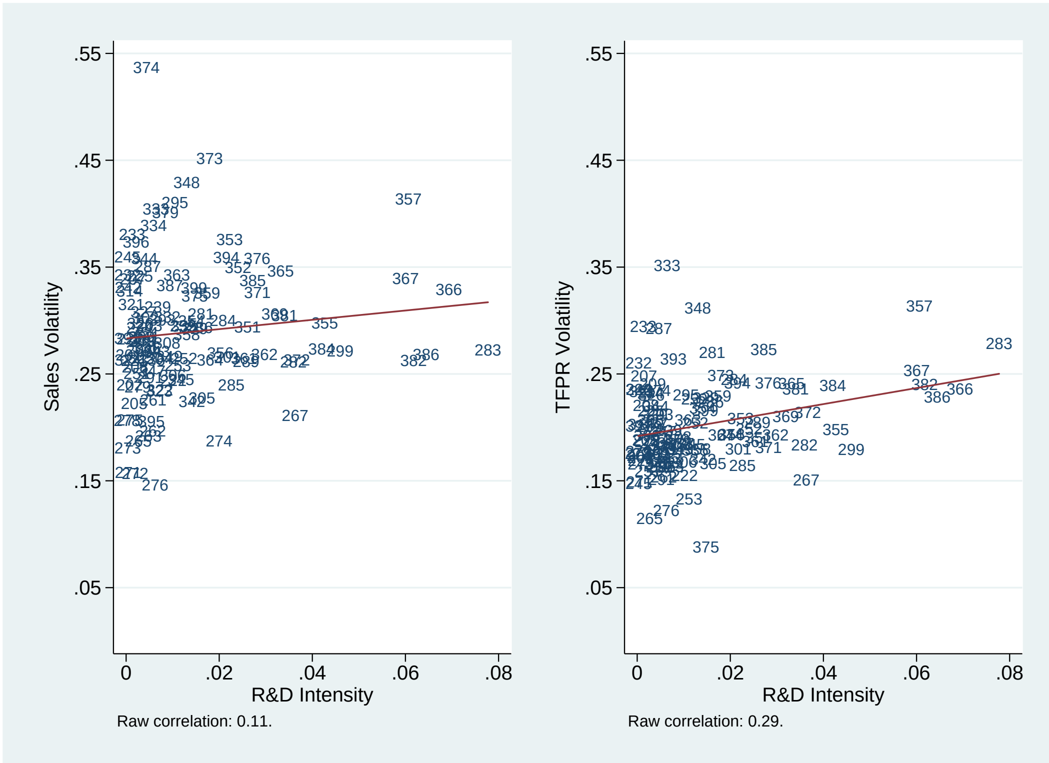


Figure 5: Idiosyncratic Risk and R&D.

Since Grilliches (1979), the relation between R&D and productivity 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 (2013). 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.

## 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 2–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.

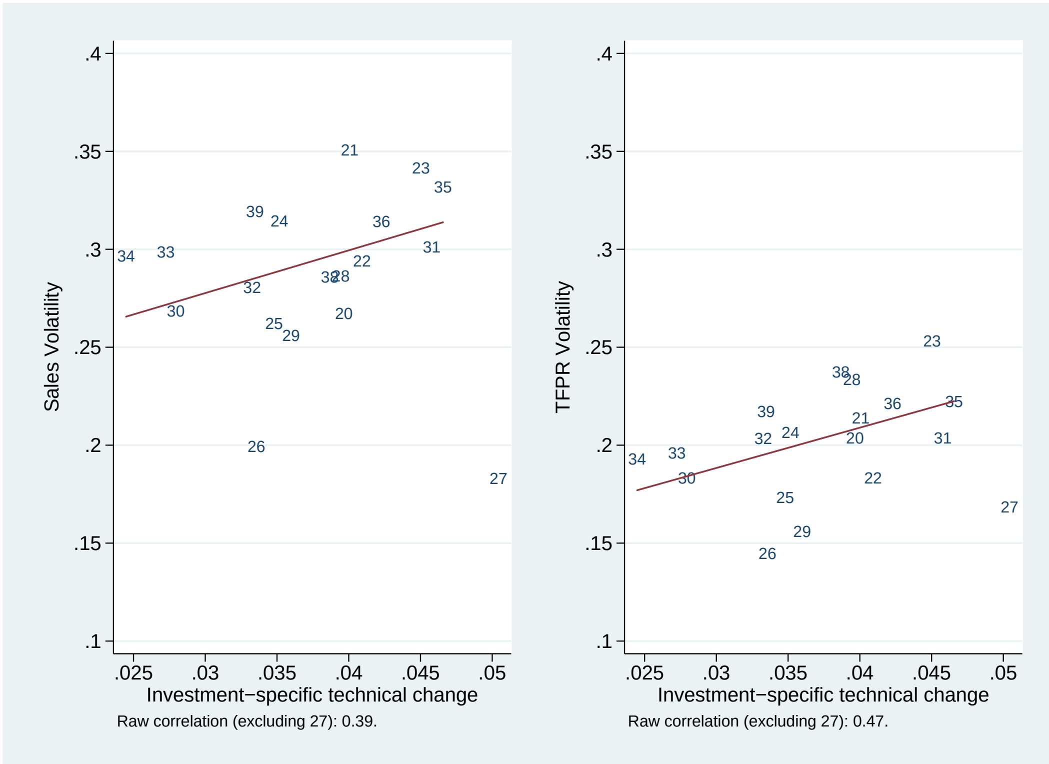


Figure 6: Idiosyncratic Risk and Investment–Specific Technological Change.

Given the level of aggregation in the data on technological change, our analysis is confined to 18 2–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 3–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 2–digit sector.[18]

The scatter plots in Figure 6 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 30 (Rubber and Miscellaneous Plastic Products), which ranks among the last sectors in terms of technological change, is also among the least uncertain.

The magnitude and statistical significance of the correlation coefficients depends

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

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

| **Dependent Variable:** | **Sales Volatility** | **TFPR Volatility** |
|---|---|---|
| ISTC | 2.1817* | 2.0579** |
| | (1.2389) | (0.8321) |
| Constant | 0.2122*** | 0.1266*** |
| | (0.0491) | (0.0317) |
| Observations | 18 | 18 |
| $R^2$ | 0.1510 | 0.2215 |

Bootstrap standard errors in parenthesis.

***Significant at 1%. **Significant at 5%. *Significant at 10%.

Note: SIC 27 excluded.

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 TFPR volatility and investment–specific technological change is 0.47, significant at the 5% confidence level. When we include the outlier, the correlation drops to 0.28, not statistically significant at the 10% level.[19]

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 we drop SIC 27, a 1 percentage point increase in ISTC growth is associated with a 2.1 percentage point increase in TFPR volatility. The estimate is significant at the 5% level.

## 5 Consumption Vs. Investment Goods

Castro, Clementi, and MacDonald (2009) argued 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

[19] With sales volatility, the correlations are 0.39 and 0.02 without and with SIC 27, respectively.

portions that meet final demand uses.

For each 3–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.[20] The details of the algorithm are in Appendix A.3.

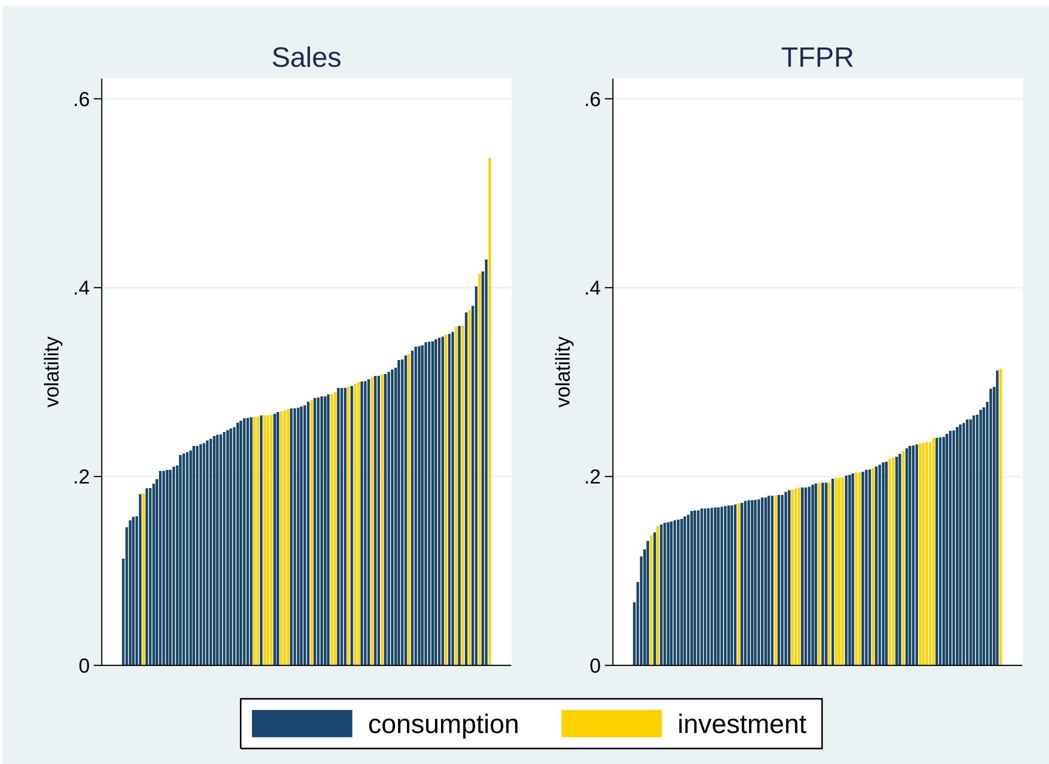


Figure 7: Volatility of sales and TFPR per 3–digit industry.

Figure 7 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 3–digit sector.

Computer equipment is the second most volatile sector. Only two investment–good sectors – Wood Buildings (245) and Stone Products (328) – are among the bottom 33 sectors in the ranking.

Formal tests confirm that on average investment–good producing plants are indeed

[20]Consumption goods are further classified as durable or non–durable.

more volatile. We run the following regression:

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

where $\alpha$ is a constant and $\theta_C$ is a dummy variable which takes value 1 if firm $i$ produces consumption goods and is zero otherwise. The average volatility is 21.63% in investment good sectors and 19.39% in consumption good industries. We can reject the hypothesis that the two estimates are equal at the 1% confidence level.[21]

Table 4: Idiosyncratic Risk and Durability

| **Dependent Variable:** | **Sales Residual** | **TFPR Residual** |
|---|---|---|
| Non-Durable Cons. Dummy | –0.3287*** | –0.0782*** |
| | (0.0201) | (0.0196) |
| Durable Cons. Dummy | –0.2011*** | –0.1837*** |
| | (0.0326) | (0.0306) |
| Constant | –4.4015*** | –5.1037*** |
| | (0.0142) | (0.0134) |
| Observations | 322,269 | 322,269 |

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

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 are almost as volatile as investment expenditures.[22] Does a similar pattern emerge at the plant level?

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

$$\ln \hat{\varepsilon}_{ijt}^{2} = \alpha + \theta_D + \theta_{ND} + u_{ijt}, \tag{5}$$

where $\theta_D$ and $\theta_{ND}$ 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

[21] With sales growth, the mean volatility among investment good–producing plants is 32.71%, while for consumption good–producing plants it is 27.32%. The difference is also statistically significant.

[22] See Stock and Watson (1999).

the assignment procedure are in Appendix A.4. The regression's results are reported in Table 4.

The point estimates suggest that TFPR volatility may actually be greater for non–durables than for durables. However, once we transform the regression coefficients to obtain the actual volatility estimates, we find that TFPR volatility is not statistically different across establishments producing durable and non–durable consumption goods. The bottom line is that we find 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 to technical efficiency, mark–ups, and input prices. 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 80% of the overall uncertainty faced by plants. We also showed that risk varies greatly across 3–digit sectors, ranging from 6.7% for producers of boot and shoe cut stock, to 35.2% for Primary Smelting and Refining of Nonferrous Metals.

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 only suggestive. Our conjecture passed a first test, but establishing causality requires a different methodological approach.

Other factors are likely to contribute to the heterogeneity that we document. Syverson (2004b) outlines a variety 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. For sure, this is the case for the parameters that drive entry and exit.

# A Data and Measurement

## A.1 Sample Construction

We start by extracting all plants in the ASM panels from 1972 to 1997. For the Census years, we use the ASM flag variable to select from the Census files the plants belonging to the ASM panels. To avoid measurement errors from the imputed variables, we follow most of the economics literature in dropping Administrative Record (AR) files. We also drop establishments with zero or missing value for employment, or shipments, or any variable needed for our estimation, such as the total cost of materials, capital expenditures on buildings or machinery, and production worker hours.

The ASM is a series of five–year panels. In the first years of the panels, the fraction of plants that can be linked longitudinally to the previous year drop dramatically as only large, continuing plants ( the so–called *certainty* cases) are included in adjacent panels. To avoid measurement issues due to panel rotation, we drop from the sample all first years of the panels.

When estimating equation (2), we drop plants with less than five observations in the sample to avoid that mis–measurement of the plant fixed effects propagate to the residuals. An increase in the cutoff did not change the key results of the paper in any appreciable way.

When estimating equation (3), we exclude sectors with less than 100 plant–year observations. This is to guarantee that the results are not driven by a relatively small number of plants in the sector.

We will make SAS and STATA programs available to researchers with access to the Census micro data, so that they can replicate the results reported in the paper.

## A.2 Variable Definitions

**Real Sales.** We use the total value of shipments (TVS) deflated by the 4–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) and choose to use the simple measure of gross output. This is to avoid potential measurement issues associated with imputations of inventories.

**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 2–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). 2–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.** Under constant returns to scale and the usual regularity conditions, cost minimization implies that each input's elasticity equals its share in total production cost. Therefore our ideal estimate of factor elasticity was the industry average cost share at the finest level of aggregation. Unfortunately capital rental rates, which are needed to compute capital costs, are only available at the 2–digit level. Following that route would have introduced a mis–specification error with potentially large consequences on our residuals' estimates.

Our solution was to set elasticities for labor and materials equal to their respective 4–digit industry–level revenue shares. The capital elasticity is set equal to the complement to 1, i.e. $\alpha^k_{\iota t} = 1 - \alpha^l_{\iota t} - \alpha^m_{\iota t}$. We use the average of revenue shares between adjacent time periods (i.e., discrete–time approximation to the Divisia index, derived from the Tornqvist index). This allows factor elasticities to vary over time.

Notice that cost shares and revenue shares coincide only when mark-ups are identically zero. In any other scenario, mis–specification is still a concern. Our view is that, however, the resulting bias is substantially lower than in the alternative described above.

In calculating labor costs, we follow Bils and Chang (2000) and adjust each 4–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 2–digit industry level. We apply the same adjustment factor to all plants within the same 2–digit industry.

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

### A.3 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.4 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 4–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 4–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 and Autoregressive Parameter Estimates

| SIC | | TFPR | | Sales | | Good Classification |
|---|---|---|---|---|---|---|
| | | Volatility | AR | Volatility | AR | |
| 333 | Primary Nonferrous Metals | 0.352 | 0.483 | 0.404 | 0.644 | |
| 357 | Computer Equipment | 0.314 | 0.548 | 0.414 | 0.672 | Investment |
| 348 | Small Arms & Ammo | 0.312 | 0.491 | 0.429 | 0.489 | Durable Consumption |
| 233 | Women's Outerwear | 0.295 | 0.464 | 0.380 | 0.599 | Other Consumption |
| 287 | Agricultural Chemicals | 0.293 | 0.420 | 0.351 | 0.567 | Other Consumption |
| 283 | Drugs | 0.279 | 0.542 | 0.273 | 0.742 | Nondurable Consumption |
| 241 | Logging | 0.278 | 0.422 | 0.381 | 0.510 | |
| 385 | Ophthalmic Goods | 0.273 | 0.427 | 0.338 | 0.561 | Durable Consumption |
| 281 | Industrial Inorganic Chems | 0.270 | 0.411 | 0.306 | 0.494 | Other Consumption |
| 236 | Girls' Outerwear | 0.265 | 0.475 | 0.345 | 0.642 | Nondurable Consumption |
| 393 | Musical Instruments | 0.264 | 0.132 | 0.301 | 0.115 | Durable Consumption |
| 232 | Men's Clothing | 0.260 | 0.496 | 0.343 | 0.566 | Nondurable Consumption |
| 238 | Misc. Apparel | 0.260 | 0.456 | 0.348 | 0.604 | Other Consumption |
| 231 | Men's Suits & Coats | 0.256 | 0.534 | 0.353 | 0.687 | Durable Consumption |
| 235 | Hats & Caps | 0.255 | 0.392 | 0.294 | 0.588 | Other Consumption |
| 367 | Elect Components & Acces | 0.253 | 0.554 | 0.339 | 0.761 | |
| 277 | Greeting Cards | 0.252 | 0.661 | 0.232 | 0.682 | Other Consumption |
| 373 | Ship&Boat Build&Repair | 0.248 | 0.375 | 0.452 | 0.541 | |

Table 5: (continued)

| SIC | | TFPR Volatility | TFPR AR | Sales Volatility | Sales AR | Good Classification |
|---|---|---|---|---|---|---|
| 311 | Leather Finishing | 0.248 | 0.269 | 0.308 | 0.455 | Other Consumption |
| 207 | Fats & Oils | 0.248 | 0.312 | 0.339 | 0.456 | Nondurable Consumption |
| 284 | Detergents & Cosmetics | 0.245 | 0.432 | 0.300 | 0.577 | Nondurable Consumption |
| 394 | Dolls, Toys, & Games | 0.242 | 0.364 | 0.359 | 0.577 | Durable Consumption |
| 376 | Guided Missiles, Space Vcl | 0.242 | 0.450 | 0.358 | 0.558 | |
| 365 | Household Audio-Video Eq | 0.241 | 0.366 | 0.347 | 0.646 | Durable Consumption |
| 209 | Misc. Food | 0.241 | 0.486 | 0.285 | 0.582 | Nondurable Consumption |
| 382 | Measuring Instruments | 0.240 | 0.390 | 0.263 | 0.594 | Investment |
| 384 | Medical Instr & Supplies | 0.239 | 0.455 | 0.273 | 0.649 | |
| 381 | Navigation Equipment | 0.236 | 0.372 | 0.305 | 0.515 | Investment |
| 366 | Communication Equipment | 0.236 | 0.441 | 0.329 | 0.610 | Investment |
| 242 | Sawmills & Planing Mills | 0.235 | 0.304 | 0.331 | 0.592 | |
| 324 | Cement, Hydraulic | 0.235 | 0.579 | 0.263 | 0.629 | Investment |
| 374 | Railroad Equipment | 0.235 | 0.267 | 0.537 | 0.311 | Investment |
| 321 | Flat Glass | 0.234 | 0.210 | 0.315 | 0.221 | Other Consumption |
| 234 | Women's Underwear | 0.232 | 0.525 | 0.294 | 0.705 | Nondurable Consumption |
| 214 | Tobacco Stemming | 0.232 | 0.339 | 0.417 | 0.744 | Other Consumption |
| 295 | Asphalt Paving & Roofing | 0.230 | 0.295 | 0.410 | 0.447 | |
| 326 | Pottery & Related Prods | 0.230 | 0.446 | 0.297 | 0.515 | |
| 359 | Industrial Machinery | 0.230 | 0.330 | 0.326 | 0.616 | |
| 317 | Handbags | 0.230 | 0.550 | 0.337 | 0.802 | Other Consumption |
| 386 | Photo Equip and Supplies | 0.228 | 0.517 | 0.268 | 0.580 | |
| 329 | Misc Nonmetal Mineral Prod | 0.227 | 0.480 | 0.292 | 0.650 | |
| 259 | Misc. Furniture | 0.227 | 0.302 | 0.295 | 0.647 | Investment |
| 286 | Organic Chemicals | 0.224 | 0.457 | 0.294 | 0.560 | Other Consumption |
| 208 | Beverages | 0.221 | 0.518 | 0.257 | 0.582 | Nondurable Consumption |
| 344 | Metal Products | 0.220 | 0.393 | 0.358 | 0.523 | Investment |
| 354 | Metalworking Machinery | 0.218 | 0.400 | 0.300 | 0.516 | Investment |
| 399 | Misc Manufactures | 0.216 | 0.100 | 0.331 | 0.196 | |
| 225 | Knitting Mills | 0.215 | 0.460 | 0.342 | 0.595 | Nondurable Consumption |
| 226 | Dyeing Textiles | 0.215 | 0.602 | 0.324 | 0.692 | Other Consumption |
| 372 | Aircraft and Parts | 0.214 | 0.498 | 0.263 | 0.581 | |
| 203 | Canned Fruits & Vegtbls | 0.212 | 0.458 | 0.296 | 0.588 | Nondurable Consumption |
| 339 | Misc Primary Metal Prods | 0.212 | 0.529 | 0.282 | 0.603 | |
| 369 | Electrical Equipment | 0.210 | 0.443 | 0.306 | 0.591 | Other Consumption |
| 353 | Construction & Mining | 0.208 | 0.492 | 0.376 | 0.583 | Investment |
| 206 | Sugar | 0.207 | 0.356 | 0.272 | 0.604 | Nondurable Consumption |
| 363 | Households Appliances | 0.207 | 0.501 | 0.343 | 0.625 | Durable Consumption |
| 289 | Misc. Chemicals | 0.205 | 0.479 | 0.262 | 0.588 | Other Consumption |
| 327 | Concrete & Plaster | 0.204 | 0.414 | 0.308 | 0.574 | Investment |
| 252 | Office Furniture | 0.204 | 0.313 | 0.264 | 0.559 | Investment |
| 314 | Footwear | 0.203 | 0.539 | 0.328 | 0.639 | Nondurable Consumption |
| 391 | Jewelry & Silverware | 0.201 | 0.528 | 0.283 | 0.713 | Durable Consumption |
| 279 | Services for Printing | 0.201 | 0.418 | 0.238 | 0.759 | Other Consumption |
| 325 | Clay Products | 0.199 | 0.477 | 0.265 | 0.545 | Investment |
| 352 | Farm Machinery | 0.198 | 0.374 | 0.350 | 0.466 | Investment |
| 355 | Special Industry Machinery | 0.198 | 0.366 | 0.298 | 0.561 | Investment |
| 239 | Misc. Textiles | 0.197 | 0.474 | 0.313 | 0.744 | Other Consumption |
| 347 | Metal Services | 0.196 | 0.344 | 0.253 | 0.663 | |
| 356 | General Industry Machinery | 0.194 | 0.417 | 0.270 | 0.551 | Investment |
| 274 | Misc. Publishing | 0.193 | 0.499 | 0.188 | 0.708 | Durable Consumption |
| 229 | Misc. Textile Goods | 0.193 | 0.481 | 0.275 | 0.664 | Other Consumption |

Table 5: (continued)

| SIC | | TFPR | | Sales | | Good Classification |
|---|---|---|---|---|---|---|
| | | Volatility | AR | Volatility | AR | |
| 364 | Elec. Lighting and Wiring | 0.193 | 0.490 | 0.263 | 0.610 | |
| 362 | Electrical Apparatus | 0.193 | 0.441 | 0.268 | 0.639 | Investment |
| 396 | Buttons & Needles | 0.192 | 0.482 | 0.374 | 0.726 | Other Consumption |
| 308 | Misc. Plastic Prods | 0.191 | 0.403 | 0.279 | 0.568 | Other Consumption |
| 351 | Engines & Turbines | 0.191 | 0.502 | 0.294 | 0.582 | |
| 379 | Misc. Transportation | 0.189 | 0.371 | 0.401 | 0.605 | Durable Consumption |
| 205 | Bakery Products | 0.188 | 0.403 | 0.222 | 0.655 | Nondurable Consumption |
| 272 | Periodicals: Publishing | 0.188 | 0.597 | 0.157 | 0.696 | Nondurable Consumption |
| 254 | Shelving & Lockers | 0.188 | 0.465 | 0.289 | 0.617 | Investment |
| 361 | Electr. Distrib. Equipment | 0.187 | 0.525 | 0.265 | 0.710 | Investment |
| 243 | Millwork | 0.186 | 0.447 | 0.281 | 0.590 | Investment |
| 387 | Watches, Clocks | 0.185 | 0.383 | 0.333 | 0.839 | Durable Consumption |
| 332 | Iron & Steel Foundries | 0.185 | 0.629 | 0.303 | 0.719 | |
| 345 | Screw Machine Prods, Bolts | 0.184 | 0.442 | 0.245 | 0.677 | |
| 282 | Plastic Materials | 0.183 | 0.455 | 0.261 | 0.559 | Other Consumption |
| 336 | Nonferrous Foundries | 0.183 | 0.460 | 0.263 | 0.676 | |
| 334 | Secondary Nonferrous Mat | 0.182 | 0.357 | 0.389 | 0.596 | |
| 371 | Motor Vehicles and Equip | 0.181 | 0.361 | 0.326 | 0.474 | |
| 349 | Misc Fabricated Metal Prod | 0.181 | 0.481 | 0.266 | 0.609 | |
| 316 | Luggage | 0.180 | 0.398 | 0.232 | 0.613 | Durable Consumption |
| 301 | Tires | 0.180 | 0.440 | 0.266 | 0.516 | Nondurable Consumption |
| 358 | Refrigeration Machinery | 0.180 | 0.392 | 0.287 | 0.551 | Investment |
| 299 | Misc. Petroleum | 0.179 | 0.531 | 0.272 | 0.621 | Nondurable Consumption |
| 261 | Pulp Mills | 0.179 | 0.338 | 0.226 | 0.349 | Other Consumption |
| 335 | Nonferrous Rolling & Draw | 0.179 | 0.504 | 0.295 | 0.611 | |
| 204 | Grain Mill Products | 0.178 | 0.289 | 0.264 | 0.474 | Nondurable Consumption |
| 273 | Books | 0.177 | 0.595 | 0.181 | 0.696 | Durable Consumption |
| 331 | Blast Furnace & Steel Prd | 0.176 | 0.396 | 0.275 | 0.459 | |
| 278 | Bookbinding | 0.176 | 0.495 | 0.207 | 0.755 | Other Consumption |
| 221 | Cotton Fabric | 0.175 | 0.328 | 0.263 | 0.663 | Other Consumption |
| 212 | Cigars | 0.175 | 0.657 | 0.259 | 0.771 | Nondurable Consumption |
| 302 | Rubber Footwear | 0.175 | 0.530 | 0.303 | 0.698 | Other Consumption |
| 201 | Meat Products | 0.174 | 0.351 | 0.268 | 0.614 | Nondurable Consumption |
| 202 | Dairy Products | 0.172 | 0.364 | 0.240 | 0.576 | Nondurable Consumption |
| 343 | Heating Equipment | 0.171 | 0.546 | 0.271 | 0.694 | Investment |
| 342 | Cutlery | 0.170 | 0.471 | 0.224 | 0.671 | Other Consumption |
| 249 | Misc. Wood Products | 0.169 | 0.408 | 0.244 | 0.543 | Other Consumption |
| 227 | Carpets & Rugs | 0.169 | 0.512 | 0.283 | 0.715 | Durable Consumption |
| 213 | Chewing Tobacco | 0.168 | 0.535 | 0.153 | 0.786 | Nondurable Consumption |
| 306 | Rubber Products | 0.168 | 0.472 | 0.249 | 0.553 | Other Consumption |
| 223 | Wool Fabric | 0.167 | 0.586 | 0.243 | 0.594 | Other Consumption |
| 322 | Glass & Glassware | 0.167 | 0.534 | 0.235 | 0.784 | Durable Consumption |
| 346 | Metal Forging | 0.166 | 0.396 | 0.274 | 0.717 | Other Consumption |
| 305 | Packing Devices | 0.166 | 0.321 | 0.227 | 0.391 | Other Consumption |
| 341 | Metal Cans | 0.166 | 0.361 | 0.285 | 0.496 | Other Consumption |
| 275 | Commercial Printing | 0.166 | 0.299 | 0.207 | 0.596 | Other Consumption |
| 285 | Paints | 0.164 | 0.600 | 0.240 | 0.709 | |
| 395 | Pens & Pencils | 0.164 | 0.408 | 0.206 | 0.544 | Other Consumption |
| 323 | Glass Products | 0.164 | 0.370 | 0.234 | 0.602 | Other Consumption |
| 263 | Paperboard Mills | 0.163 | 0.446 | 0.192 | 0.437 | Other Consumption |
| 251 | Household Furniture | 0.159 | 0.469 | 0.251 | 0.769 | Durable Consumption |
| 228 | Yarn & Thread Mills | 0.157 | 0.431 | 0.311 | 0.635 | Other Consumption |

Table 5: (continued)

| SIC | | TFPR | | Sales | | Good Classification |
|---|---|---|---|---|---|---|
| | | Volatility | AR | Volatility | AR | |
| 222 | Silk Fabric | 0.155 | 0.491 | 0.244 | 0.693 | Other Consumption |
| 224 | Narrow Fabric | 0.154 | 0.383 | 0.252 | 0.779 | Other Consumption |
| 262 | Paper Mills | 0.153 | 0.463 | 0.197 | 0.571 | Other Consumption |
| 244 | Wood Containers | 0.152 | 0.309 | 0.287 | 0.662 | Other Consumption |
| 291 | Petroleum Refining | 0.151 | 0.377 | 0.247 | 0.582 | Nondurable Consumption |
| 267 | Converted Paper Prods | 0.151 | 0.509 | 0.211 | 0.678 | Other Consumption |
| 271 | Newspapers: Publishing | 0.149 | 0.409 | 0.158 | 0.312 | Nondurable Consumption |
| 245 | Wood Buildings | 0.147 | 0.379 | 0.360 | 0.610 | Investment |
| 319 | Other Leather Goods | 0.141 | 0.331 | 0.206 | 0.746 | Other Consumption |
| 328 | Stone Products | 0.137 | 0.567 | 0.182 | 0.515 | Investment |
| 253 | Public Bldg Furniture | 0.133 | 0.515 | 0.258 | 0.601 | |
| 315 | Leather Gloves | 0.132 | 0.459 | 0.210 | 0.331 | Other Consumption |
| 276 | Business Forms | 0.122 | 0.377 | 0.146 | 0.744 | Other Consumption |
| 265 | Paperboard Containers | 0.115 | 0.526 | 0.187 | 0.626 | Other Consumption |
| 375 | Motorcycles, Bicycles | 0.088 | 0.184 | 0.323 | 0.871 | Durable Consumption |
| 313 | Boot & Shoe Cut Stock | 0.067 | 0.712 | 0.113 | 0.496 | 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 |

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