Market Exposure and Endogenous Firm Volatility over the Business Cycle*

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Abstract

We propose a theory of endogenous firm-level volatility over the business cycle based on endogenous market exposure. Firms that reach a larger number of markets diversify market-specific demand risk at a cost. The model is driven only by total factor productivity shocks and captures the business cycle properties of firm-level volatility. Using a panel of U.S. firms (Compustat), we empirically document the countercyclical nature of firm-level volatility. We then match this panel to Compustat's Segment Data and the U.S. Census Bureau's Longitudinal Business Database (LBD) to show that, consistent with our model, measures of market reach are procyclical and the countercyclicatility of firm-level volatility is driven mostly by those firms that adjust the number of markets to which they are exposed. This finding is explained by the negative elasticity between various measures of market exposure and firm-level idiosyncratic volatility we uncover using Compustat, the LBD, and the Kauffman Firm Survey.

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1 Introduction

The objective of this paper is to explain the countercyclicality of firm-level volatility observed in the data. We propose a theoretical model in which firms endogenously determine the number of markets in which they participate and thereby expose themselves to market-specific demand shocks. As long as the market-specific shocks are not perfectly correlated, the endogenous expansion of market exposure implies changes in firm-level volatility. We test the model empirically and find that its implications are consistent with how firm-level risk evolves over the business cycle and correlates to measures of market exposure.

Consistent with our findings, the empirical literature has found that various measures of uncertainty are countercyclical. In a seminal paper, Bloom (2009) proposes a mechanism where exogenous changes in uncertainty (or second moment shocks) are key drivers of the business cycle. In this paper, we evaluate the possibility that causality operates in the opposite direction. Our hypothesis is that part of the observed change in measured uncertainty over the business cycle is an endogenous response to first moment shocks.

To understand observed patterns of cyclical risk, we construct a simple model of market participation.[1] In this model, a representative consumer derives utility from the consumption of market-specific goods that are imperfect substitutes. The consumer faces market-specific taste shocks that result in stochastic market demands. A continuum of competitive firms differ in their level of idiosyncratic productivity and face an aggregate productivity shock. They can sell to many markets by incurring selling expenses that are increasing in the total number of markets that a firm services and are incurred before taste shocks are realized. Thus, these endogenous per-period sunk costs determine the pool of suppliers in each market.

Though the firms in our model are risk neutral and lack any risk diversification objective, we find that they increase their revenues and diversify market-specific shocks by reaching more markets. This generates the negative relationship between measures of market exposure and firm-level risk that is observed in the data. Also consistent with the evidence, large firms (*i.e.,* high-productivity firms) expand to more markets than small firms, making them less volatile. More importantly, incentives to expand are higher in good times (*i.e.,* when aggregate productivity is high) than in bad times. This allows the model to capture the procyclicality of market participation measures and, because a larger market exposure results in lower firm-level volatility, the observed countercyclicality of dispersion of firm-level risk.

[1] We adopt a broad definition of "market" that applies to the market-product space, the market-location space, and a combination of the two. The empirical measures we use are intended to capture this broad definition of market.

The countercyclicality of firm-level risk has been documented by Bachmann and Bayer (2011a and b). The model is also consistent with the evidence at levels of aggregation other than that of the firm. First, it captures the fact that the distribution of prices is countercyclical as described in Berger and Vavra (2011). Second, it generates a countercyclical dispersion of plant-level productivity as reported by Kehrig (2011). Finally, the model captures the fact that firm-level market exposure is procyclical. This has been documented by Broda and Weinstein (2010) based on the number of products per firm (derived from bar code data) over the cycle. We also find that the number of establishments per firm, another correlate of market exposure (especially for large firms), is procyclical.

The contribution of our empirical analysis is to document the relationship between firm-level risk and several measures of market participation, as well as their cyclical properties. As in Castro, Clementi, and MacDonald (2009), we measure firm-level idiosyncratic risk as the portion of growth in sales that cannot be explained by firm-level characteristics (such as age or size), industry, or year effects. The core dataset for our empirical analysis is Compustat (a long panel of large, public U.S. firms). We construct two samples based on the core Compustat file: in one sample, we match Compustat with Compustat Segment or "line of business" data; in another sample, we add matched firm-year data from the U.S. Census Bureau's Longitudinal Business Database (LBD).[2] The Compustat-Segment data provide one of our direct measures of firms' market exposure. As described in Bloom, Schankerman and Van Reenen (2013), this data set contains information on each self-reported product market a firm operates at annual frequency by splitting firms' sales by four-digit SIC product codes. Additionally, from the LBD we obtain the number and location of establishments for each firm (also at annual frequency). Moreover, Compustat contains information on less direct measures of market participation. In particular, we obtain data on selling expenses, which the model uses as the main determinant of the number of markets a firm operates. We focus on selling and general expenses (SGA) since they refer to expenses on, for example, advertising, marketing, brand development, and research and development. These expenses are large in magnitude: they represent, on average, 17 percent of sales (in our sample) or between 10 and 13 percent of GDP as reported by Corrado, Hulten and Sichel (2005). Finally, we complement this panel of large public firms with the Kauffman Firm Survey (KFS). This allows us to capture firms on opposite end of the size distribution since KFS focuses on small, entrepreneurial firms. Unfortunately, the KFS sample is too short to derive business cycle properties, but we still derive our measure of firm-level risk and uncover its

[2] See the following section as well as the Appendix for a detailed description of each data source and the matching procedure.

link with measures of market expansion.

Our main empirical findings are that volatility is countercyclical (having correlation with detrended GDP equal to -0.46). Consistent with our model, we find that this negative correlation is mostly driven by those firms that adjust the number of markets they operate over time and that our direct as well as indirect measures of market expansion are procyclical. Specifically, among firms that adjust market exposure the correlation between firm-level risk and detrended GDP is between -0.311 and -0.422 depending on our market definition, while risk is acyclical for firms that do not adjust. We also find that the change in the number of markets (when measured by product market and by location market) and selling expenditures are both procyclical, especially for the largest firms. Finally, we show that the elasticity of firm-level risk to all of our measures of market expansion is negative and significant, ranging from -7.5 to -30.1 percent.

Our paper is related to previous work analyzing the possibility of reverse causation between measured uncertainty and business cycles which has already been documented by Bachmann, Elstner, and Sims (2013)[3]. We offer an alternative explanation to Van Nieuwerburgh and Veldkamp (2006), Bachmann and Moscarini (2011), and Tian (2012). In Van Niewerburgh and Veldkamp (2006), procyclical learning about productivity generates the observed countercyclicality in firm-level volatility. In Bachmann and Moscarini (2011), downturns offer the opportunity to experiment and learn the firm-specific demand function; that experimentation is the driver of additional volatility. In Tian (2012), periods of recession are accompanied by more risk-taking behavior at the firm level. In our model, positive first moment shocks (TFP) enable firms to expand to more markets and expose firms to an increased number of market-specific shocks, reducing volatility through a standard diversification mechanism.

This work brings together two relatively recent streams in the literature. The first is the literature regarding business cycles and uncertainty started with the work by Bloom (2009) but also including Arellano, Bai, and Kehoe (2011), Bloom et al. (2011), Christiano, Motto, and Rostagno (2011), Chugh (2012), and Schaal (2012). In contrast with our paper, in this literature exogenous changes in volatility are key to generating business cycles. The second stream of the literature is comprised of studies that empirically analyze firm-level risk. Castro, Clementi and Lee (2011) attribute differences in firm-level volatility to differences in the sectors in which firms operate. In contrast, we uncover the relationship between firm-level volatility and total market exposure and associated intangible expenses (after controlling for

[3]Baker and Bloom (2013) tackle the issue of causality between first and second moment shocks using disasters as natural experiments, finding that both are significant in explaining GDP growth.

industry effects). Comin and Philippon (2005) document the increasing trend in firm-level volatility using Compustat, whereas Davis et al. (2006) show that the increase in firm-level risk is related to a selection issue, since public firms are more volatile.

The notion that agents are exposed to a limited number of shocks and therefore the law of large numbers does not apply is not unique to our work. Among the papers that use this assumption are Gabaix (2011), Acemoglu et al. (2011), and Koren and Tenreyro (2011). These papers argue that a small group of firms (as in Gabaix (2011)), a small number of sectors (as in Acemoglu et al. (2011)), or a small number of inputs (as in Koren and Tenreyro (2011)) are the drivers of aggregate volatility.

We also build on the literature on multi-product firms. For example, Bernard, Redding, and Schott (2010) allow for the endogenous expansion of the firm but do not consider the risk dimension of this activity. Other related papers include Arkolakis (2010), Bloom et al. (2010), and Gourio and Rudanko (2011). Arkolakis (2010) develops a model of customer capital through advertisement—which is one of the elements of our intangible expenditures measure. Bloom et al. (2010) measure the effects of management expenditures (also within our definition of intangibles) on Indian firms, and Gourio and Rudanko (2011) develop a search model to analyze how intangible expenses affect firm dynamics.

The paper is organized as follows: Section 2 presents the empirical facts regarding the risk distribution across firms and over the business cycle, using Compustat and Kauffman Foundation data. Sections 3 and 4 present a firm dynamics model with endogenous expansion and contraction of firms to capture the evidence presented in Section 2. Section 5 calibrates the model to the distribution of firms in the U.S. Section 6 discusses the effects of total factor productivity changes and derives a set of testable implications. Section 7 examines the evidence, guided by the model outcomes, and uncovers the relationship between volatility and measures of market exposure as well as their cyclical properties. Finally, Section 8 concludes.

2 Idiosyncratic Risk Facts

The goal of this study is understanding the determinants of cross-sectional variation in firm-level idiosyncratic risk and its relationship with the business cycle. In this section, we present evidence on the level of idiosyncratic risk and its cyclical components. These are well-known facts in the literature; specifically, firm-level risk is countercyclical and is related to firm size (larger firms tend to be less volatile).

Our main empirical facts come from Compustat and consist of annual accounting data for publicly listed U.S. firms.[4] We use data from 1960 to 2012, consisting of an unbalanced panel of more than 8,400 firms for a total of 241,308 firm-year observations. Compustat data are subject to selection bias as described by Davis et al. (2006). Because these firms are relatively larger and older than those that are not in Compustat, they are likely to be less volatile (see Castro, Clementi and Lee (2011)). We try to address these differences by controlling for age and size and by using the Kauffman Firm Survey (KFS), a sample of small firms, to derive some of our results.[5] The KFS is a large panel of "young" businesses. Firms in the sample were founded in 2004 and have been tracked annually.[6] This panel was created using a random sample from Dun and Bradstreet's database of new businesses. The target population consisted of new businesses that were started in 2004 in the United States and excludes any branch or subsidiary that was owned by an existing business or was inherited from someone else. The sample for the first survey consisted of 4,928 businesses.

As in Castro, Clementi, and MacDonald (2009) our proxy for firm-level idiosyncratic risk is the volatility of the portion of growth in sales that is not explained by industry effects, time effects, or firm characteristics associated with growth such as age or size (measured by employment).[7,8] The first step toward obtaining our measure of idiosyncratic volatility is to estimate the following equation:

$$\Delta \ln(sales_{ijt}) = \mu_i + \delta_{jt} + \beta_{1j} \ln(size)_{ijt} + \beta_{2j} \ln(age)_{ijt} + \epsilon_{ijt}, \tag{1}$$

where $\Delta \ln(sales)_{ijt}$ is the growth of real sales for firm i, in industry j, between period t and period $t+1$. The variable μ_i is a firm fixed effect that accounts for unobserved persistent

[4] Appendix A1 provides a detailed description of our sample and of the construction of the key variables and the matching procedure.

[5] As we discuss in Section 7, we combine Compustat with Segment data and the U.S. Census Bureau's Longitudinal Business Database (LBD) to provide direct evidence on the mechanism of the model. While the LBD contains nearly every firm in the economy, it does not provide information on total revenues at the firm level (and, regardless, we only report results from LBD firms that have been matched to Compustat data). The Census Bureau datasets, such as the Longitudinal Research Database (LRD), includes revenue data but consist of limited samples for specific sectors only. These limitations prevented us from conducting the full experiment (all sectors, all firms) using only the LBD and/or the other data sources.

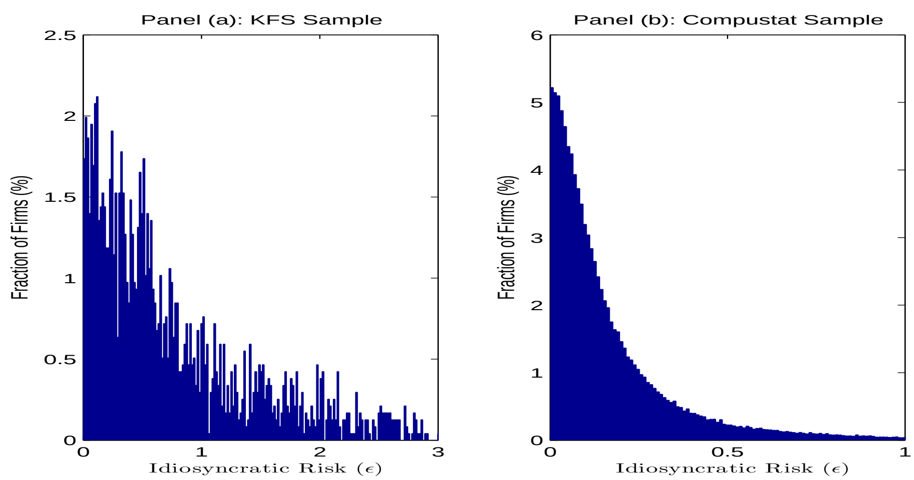
[6] Data are currently available for the years through 2008. See http://www.kauffman.org/kfs/ for a detailed description of the data and for the public-use microdata itself.

[7] Results are robust to a measure of idiosyncratic risk derived from total factor productivity at the firm level. However, due to measurement issues associated with physical capital and factor shares in Compustat and the Kauffman Firm Survey, our preferred firm-level volatility measure is based on sales growth. TFP results are available upon request.

[8] We are able to explicitly control for age in our Compustat sample; however, because all firms in the KFS are of the same age (all firms are born in 2004), this effect is already factored in.

heterogeneity at the firm level (such as higher productivity, higher human capital of the entrepreneur, etc). The variable δ_{jt} denotes a full set of time- and industry-specific fixed effects.[9] We allow for industry-specific size effects. The estimation of equation (1) is done using the fixed effects panel estimator with robust standard errors. In the KFS sample, we use revenues from sales of goods, services, or intellectual properties as our measure of sales. In the Compustat sample, our measure of sales is item #12, *net sales*.[10] Size, as is standard in the literature, is defined in both samples as the number of employees. Age corresponds to the time since a firm first appeared in the sample.

Figure 1: Idiosyncratic Dispersion



Note: Data from KFS and Compustat. Idiosyncratic Dispersion based on sales growth.

Once equation (1) is estimated, we can compute the error, or the pure idiosyncratic and unpredictable component of firms' sales growth, ϵ_{ijt}. Following Castro, Clementi and MacDonald (2009), we proxy firm-level volatility by ϵ_{it}^2.[11] Figure 1 presents the estimated

[9] We use two-digit NAICS codes for firms in our KFS and Compustat sample.

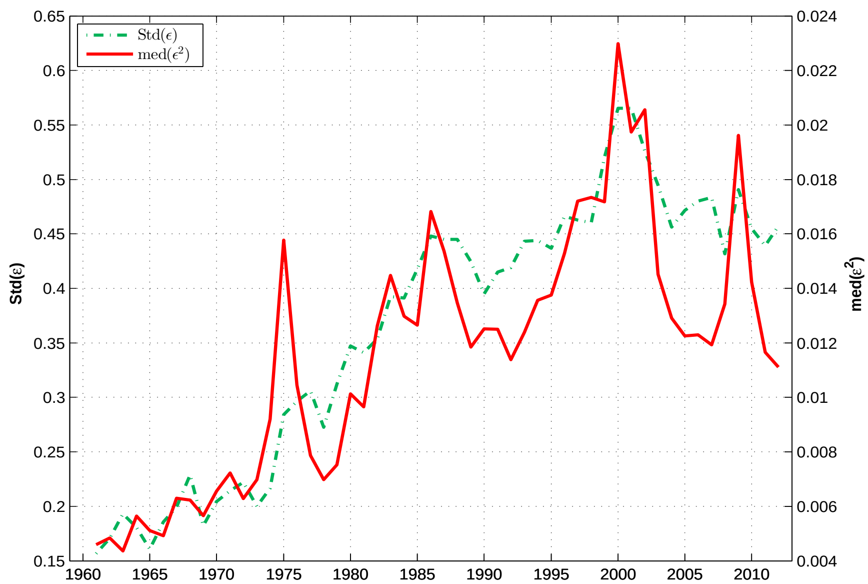
[10] The sample selection and the definition of all variables used in the analysis are described in detail in Appendix A1. Nominal variables are deflated using the BEA's two-digit sector-specific price deflator for value added.

[11] This measure of volatility is consistent with a multiplicative heteroscedasticity model (see Harvey (1976)). More specifically, this formulation results from assuming that σ_{ijt}^2, the variance of the disturbance in equation (1) (*i.e.,* the variance of ϵ_{ijt}), takes the following form: $\sigma_{ijt}^2 = \exp(\alpha Z_{ijt}')$ where Z_{ijt} is a $p \times 1$ vector of observations on a set of variables which are usually, though not necessarily, related to the regressors in (1), and α is a $p \times 1$ vector of parameters. One advantage of this identifying assumption is that it provides a firm-level measure of volatility every year. We show in this section that aggregate facts are similar to those derived from the evolution of the cross-sectional standard deviation of ϵ_{ijt}.

distribution of idiosyncratic volatility for both samples. We note that firms in the KFS sample show considerably more volatility that those in the Compustat sample. This is consistent with the evidence presented in Haltiwanger et al. (2010). The median dispersion in the KFS is more than five times the median dispersion in the Compustat sample. The estimated dispersion for the Compustat sample is consistent with the estimates in Castro, Clementi and MacDonald (2009) and Castro, Clementi and Lee (2011).

We now analyze how firm-level volatility moves over the business cycle. Figure 2 shows the evolution of the cross sectional standard deviation of ϵ_{ijt} and of median $\ln(\epsilon_{ijt}^2)$.

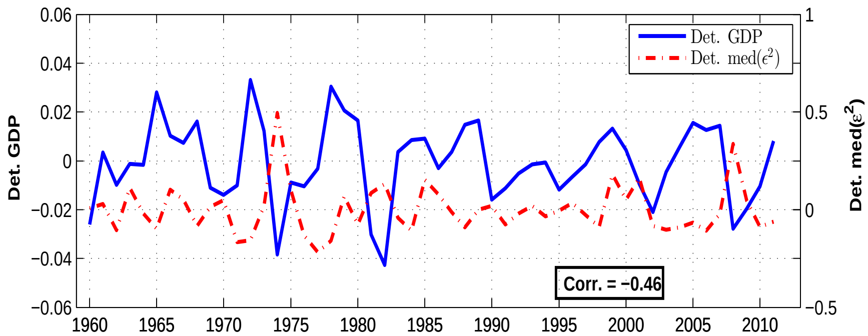
Figure 2: Evolution of Idiosyncratic Risk

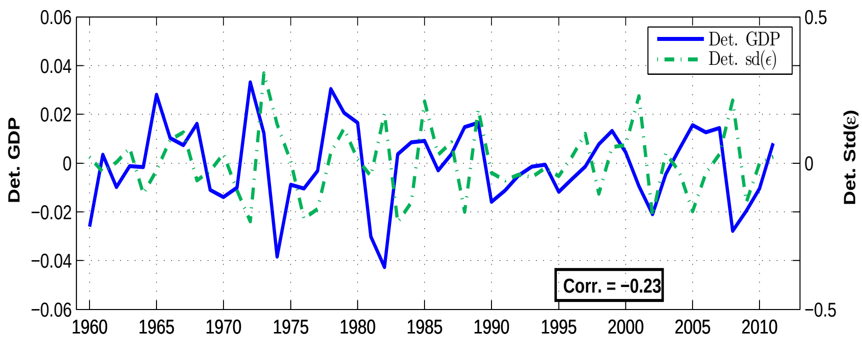


Note: Data source is Compustat. This figure shows the cross sectional standard deviation of ϵ_{ijt} and median $\ln(\epsilon_{ijt}^2)$ where ϵ_{ijt} is the unexplained portion of sales growth from equation (1).

Consistent with the estimates in Comin and Philippon (2005) and Davis et al. (2006), we find that idiosyncratic risk for publicly traded firms increased for several decades until the early 2000s. Figure 3 shows the relationship between detrended log real GDP and two different aggregate measures of idiosyncratic risk: detrended log median ϵ_{ijt}^2 and detrended cross-sectional standard deviation of ϵ_{ijt}.

Figure 3: Idiosyncratic Dispersion and Business Cycles





Note: Firm-level data source is Compustat. Real GDP is from Fred Economic Data (St. Louis Federal Reserve Bank). This figure shows the correlation between detrended log real GDP with detrended cross sectional standard deviation of ϵ_{ijt} and median $\ln(\epsilon_{ijt}^2)$, where ϵ_{ijt} is the unexplained portion of sales growth from equation (1). All variables are detrended using the H-P filter with parameter 6.25.

The correlation of real GDP with median $\ln(\epsilon_{ijt}^2)$ and cross sectional standard deviation of ϵ_{ijt} (our estimated measure of idiosyncratic risk) equals -0.46 ($p-$value=0.00) and -0.23 ($p-$value=0.09), respectively. The 10% confidence interval for these correlations is $[-0.62, -0.26]$ and $[-0.44, -0.01]$.[12] The finding of countercyclical risk at the firm level is common in the literature. A survey of this literature can be found in Bloom and Fernandez-Villaverde (2012).

In what follows, we will explore the relationship between volatility, market exposure, and expenses in more detail through the lens of our model.

[12]We present our results based on median $\log(\epsilon_{ijt}^2)$ and cross sectional standard deviation of ϵ_{ijt}. Results are robust to different definitions of volatility. In particular, the correlation of the average $\log(\epsilon_{ijt}^2)$ with Det. GDP is =-0.22 (significant at the 10% level) and the correlation of the sales-weighted standard deviation of ϵ_{ijt} with detrended GDP is -0.09 (significant only at the 25% level).

3 Environment

We study an economy with N markets (where N is large but finite), a representative consumer, and a continuum of competitive firms. Time is discrete, and a period is set to one year. Firms can service each of the different markets by incurring sales and marketing expenses. We interpret a market to be a location-product pair.

3.1 Households Preferences and Endowments

The representative household derives utility from the consumption of the composite good C_t. More specifically, their preferences are given by $U(C_t)$ where C_t is a composite of the consumption goods associated with each market n:

$$C_t = \left[\sum_{n=1}^{N} \left(\xi_{n,t} c_{n,t} \right)^{\rho} \right]^{1/\rho}, \ 1 > \rho > 0, \tag{2}$$

where $c_{n,t}$ refers to consumption in market n, $\xi_{n,t}$ is a taste shock associated with market n in period t, and $1/(1-\rho) > 1$ is the elasticity of substitution among different markets.[13] It is assumed that $\log(\xi_{n,t}^{\frac{\rho}{1-\alpha\rho}}) \sim N(0, \sigma_\xi^2)$, where α is the degree of decreasing returns to scale in production[14].

The household is endowed with one unit of labor that it supplies inelastically every period at wage w_t and receives dividends D_t through ownership of firms in the economy[15].

The ideal Dixit-Stiglitz price index is then,

$$P_t = \left[\sum_{n=1}^{N} \left(\frac{p_{n,t}}{\xi_{n,t}} \right)^{\frac{\rho}{\rho-1}} \right]^{\frac{\rho-1}{\rho}}. \tag{3}$$

Thus, the budget constraint that consumers face is

$$P_t C_t \leq w_t + D_t. \tag{4}$$

Foster, Haltiwanger and Syverson (2012) find that a large part of the differences across firms is better explained by demand factors than productivity; we base our model's demand

[13]We adopt a broad definition of market that applies to the market-product and market-location space and/or a combination of the two.

[14]This normalization of the exponent of $\xi_{n,t}$ only makes the analysis cleaner further down

[15]Note that firms will make profits given the assumption of decreasing returns to scale.

shock setup on this observation.[16]

3.2 Firms and Technology

Firms are described by their productivity parameter s, which is constant over time. Production requires only one factor, labor. Given aggregate productivity z_t, a firm that has productivity s and supplies to market n produces with technology given by

$$q_{n,t}(s) = z_t s \ell_{n,t}^{\alpha}, \tag{5}$$

where $\ell_{n,t}$ is labor employed in the production of goods in period t. We assume that firm-level productivity takes values on a finite set S, is drawn from a distribution with pdf equal to $\mu(s)$, and is constant over the lifespan of the firm.

Firms can reach and sell to consumers in market n by incurring sales, marketing, and other intangible expenses. We assume that these expenses are measured in units of labor and are increasing in the number of markets that the firms serve.[17] The total cost paid, measured in labor units, by a firm that serves m markets is $w_t\Phi_t(m) = w_t\frac{\psi}{z_t}(m-1)^{1+\nu}$. As we show below, firms have incentives to participate in more markets to access more customers; this results in diversification of market-specific risk even though diversification is not in the firm's objective function. We are assuming that the firm runs an establishment (or has a physical presence) per location/market it serves (a reasonable assumption for most industries with the possible exceptions of manufacturing, online trade, and parts of finance and insurance and information). The assumption that marketing and sales expenses are increasing in the number of markets that the firm serves reflects the notion that complexity in management is tied to some resource that is in fixed supply. Intangibles are treated as expenditures in the model, which is a reflection of their large depreciation rate. Landes and Rosenfield (1994) observe that, for advertising, the annual depreciation rate was between 55 and 100 percent. Note that the aggregate shock z_t appears in the expansion cost function, as we assume that workers in market expansion endeavors are affected by changes in z_t just as are workers in production. That is, we analyze the impact of productivity changes affecting all the inputs in the economy and not a relative change of productivity in production vs. management technology.

[16]Our model can also be interpreted as one where the shocks are location-specific productivity shocks, with an immobile labor force and perfectly flexible demand.

[17]One interpretation of the demand differences corresponds to geographical distance or differences in products. Another interpretation is an increasing cost that arises from the complexity of serving many markets.

Firms maximize dividends, acting as price takers in each location in which they participate.

3.3 Timing

The timing within a period is as follows:

1. z_t is realized.
2. Firms choose the number of markets in which to operate.
3. Taste shocks $\xi_{n,t}$ are realized.
4. Taking prices as given, firms choose labor and produce.
5. Households consume.

This assumed timing is convenient because it abstracts from the specific market in which the firm chooses to participate and simplifies the problem to choosing the number of markets the firm wants to reach as a function of the aggregate productivity z_t and its own idiosyncratic productivity s. These assumptions imply that the solution to the dynamic problem of the firm boils down to solving a sequence of one-period problems.

4 Equilibrium

This section presents a Competitive Equilibrium.

4.1 Consumer's Problem

The household's optimal conditions imply that its demand for consumption good in location n in period t is:

$$c_{n,t} = \xi_{n,t}^{\frac{\rho}{1-\rho}} \left(\frac{p_{n,t}}{P_t^{\rho}}\right)^{\frac{1}{\rho-1}} [w_t + D_t] \tag{6}$$

4.2 Firm's Problem

Firms are perfect competitors in each market in which they participate. It is most intuitive to start by solving the firm's problem at the production stage then to derive the optimal condition for the number of markets. After the shocks z_t and $\xi_{n,t}$ are revealed, the firm optimizes over the amount of labor to demand in each market they have previously chosen to serve.

The profit function for a firm in market n is given by:

$$\pi_{n,t}(s) = \max_{l_{n,t}} \{p_{n,t} q_{n,t}(s) - w_t l_{n,t}\} \tag{7}$$

subject to

$$q_{n,t}(s) = z_t s \ell_{n,t}^{\alpha}, \tag{8}$$

This delivers a standard labor demand in market n for a firm with productivity s,

$$l_{n,t}(s) = \Big(\frac{w_t}{p_{n,t} s z_t \alpha}\Big)^{\frac{1}{\alpha-1}} \tag{9}$$

This implies that profits for a firm with productivity s in market n are the following:

$$\pi_{n,t}(s) = (p_{n,t} s z_t)^{\frac{1}{1-\alpha}} w_t^{\frac{\alpha}{\alpha-1}} (\alpha^{\frac{\alpha}{1-\alpha}} - \alpha^{\frac{1}{1-\alpha}}). \tag{10}$$

At the beginning of the period (*i.e.*, before $\xi_{n,t}$ are revealed but after firms observe z_t), using the previous expression in expected value, firms can derive the optimal number of markets they would like to serve. More specifically, firms enter the m^{th} market as long as

$$E(\pi_{m,t}(s)) \geq w_t \Big(\Phi(m) - \Phi(m-1)\Big). \tag{11}$$

In other words, the firm will expand to m markets as long as the expected profit in the last market is larger that the additional cost required to manage the last market. We denote by $m_t(s)$ the number of markets in which each firm, of productivity s, chooses to participate in period t[18].

[18] Our convexity assumption on the cost function $\Phi(m)$ ensures that the solution to the firm's problem is unique

4.3 Definition of Equilibrium

In any given period t, a Competitive Equilibrium is a set of labor $l_{n,t}(s)$ and number of markets $m_t(s)$ decision rules, a wage rate w_t, a vector of goods prices $\{p_{n,t}\}_{n=1}^{N}$, and a vector of distributions of firms with productivity s, participating in each market n, $\{\lambda_{n,t}(s)\}_{n=1}^{N}$, such that

1. At the given wage rate, prices, each firm's labor decision rule, and each firms's optimal number of markets are the solution to problems (7) and (11).

2. The distribution of firms in market n equals

$$\lambda_{n,t}(s) = \frac{\mu(s)m_t(s)}{N}.$$

3. The labor market clears, that is

$$\sum_{s=\underline{s}}^{\overline{s}} \sum_{n=1}^{N} \lambda_{n,t}(s) l_{n,t}(s) + \sum_{s=\underline{s}}^{\overline{s}} \mu(s)\Phi(m_t(s)) = 1. \tag{12}$$

4. The price $p_{n,t}$ is such that it clears the n^{th} market, that is,

$$\sum_{s=\underline{s}}^{\overline{s}} \lambda_{n,t}(s) q_{n,t}(s) = c_{n,t} \tag{13}$$

   where $c_{n,t}$ is given by equation (6).

5. Aggregate dividends are

$$D_t = \Pi_t - w_t \sum_{s=\underline{s}}^{\overline{s}} \mu(s)\Phi_t(m_t(s)), \tag{14}$$

   where Π_t denotes the sum of profits across markets and is given by

$$\Pi_t = \sum_{s=\underline{s}}^{\overline{s}} \sum_{n=1}^{N} \lambda_{n,t}(s)\pi_{n,t}(s). \tag{15}$$

With this definition established, we can characterize firms' behavior and the aggregate equilibrium objects.

4.4 Characterization of the equilibrium

From the price market clearing condition (equation (13)) and the optimal demand of goods (equation (6)), the equilibrium price in market n is

$$p_{n,t} = \xi_{n,t}^{\frac{\rho(1-\alpha)}{1-\alpha\rho}} A_t, \tag{16}$$

where $A_t = \left[P_t^{\rho} \left(\frac{(w_t + D_t) w_t^{\frac{\alpha}{1-\alpha}}}{\widetilde{s}_t z_t^{\frac{1}{1-\alpha}} \alpha^{\frac{\alpha}{1-\alpha}}} \right)^{1-\rho} \right]^{\frac{1-\alpha}{1-\alpha\rho}}$ and $\widetilde{s}_t = \frac{1}{N} \sum_{s=\underline{s}}^{\overline{s}} \mu(s) m_t(s) s^{\frac{1}{1-\alpha}}$. Note that A_t is a function of aggregate productivity as well as the endogenous wage. Under the calibrated parameters shown below, A_t is countercyclical and is one of the driving forces of the countercyclicality of the dispersion of prices across markets.

Combining the equation that determines the number of markets for a given firm of productivity s (equation (11)) and using the equation of the market clearing price in market n just derived, we find that firms will enter market m only if

$$\underbrace{s^{\frac{1}{1-\alpha}} B_t}_{\text{Expected Marginal Profit}} \geq \underbrace{w_t \Big(\Phi(m) - \Phi(m-1) \Big)}_{\text{Marginal Cost}} \tag{17}$$

where $B_t = e^{\frac{\sigma_\xi^2}{2}} z_t^{\frac{1}{1-\alpha}} w_t^{\frac{\alpha}{\alpha-1}} \Big(\alpha^{\frac{\alpha}{1-\alpha}} - \alpha^{\frac{1}{1-\alpha}} \Big) A_t^{\frac{1}{1-\alpha}}$. The expected marginal profit has two components; one is firm-specific and is a function of its productivity s, and the other has to do with the economy as a whole and depends on parameters in time t (such as the wage rate w_t and aggregate productivity z_t). The larger the firm-specific productivity, the larger the expected profit given the assumption of decreasing returns to scale. The effects from the economy-wide parameters go in the following direction: higher levels of aggregate productivity generate higher expected profits while higher wages reduce expected profits. Both aggregate effects are multiplied by the firm-specific productivity, generating an asymmetric response of productivity to the aggregate environmental parameters.

The labor market clearing condition (equation (12)) implies that

$$\begin{aligned} w_t + D_t &= \frac{w_t}{\alpha} \left[1 - \sum_{s=\underline{s}}^{\overline{s}} \mu(s) \Phi(m_t(s)) \right] \\ \Rightarrow \frac{\Pi_t}{w_t} &= \left[1 - \sum_{s=\underline{s}}^{\overline{s}} \mu(s) \Phi(m_t(s)) \right] \Big(\frac{1}{\alpha} - 1 \Big), \end{aligned}$$

so, in equilibrium, the price index P_t becomes

$$P_t = \left[\frac{1 - \sum_{s=\underline{s}}^{\overline{s}} \mu(s)\Phi(m_t(s))}{\widetilde{s}_t}\right]^{1-\alpha} \frac{w_t}{\alpha z_t} \left(Ne^{\frac{\sigma_\xi^2}{2}}\right)^{\frac{\alpha\rho-1}{\rho}}. \tag{18}$$

To solve for an equilibrium, we need to solve a system of three aggregate equations ((12),(14),(15)) and three unknowns $\{\sum_{s=\underline{s}}^{\overline{s}} \mu(s)\Phi(m_t(s)),\ w_t,\ \widetilde{s}_t\}$, such that they are consistent with firm-level decisions.

4.4.1 Elasticity of Firm/Plant-Level Volatility and Business Cycle Properties

In this section, we analyze the coefficient of variation of TFPR at the firm level because it gives a compact expression that is useful for building intuition.[19] Conditional on the aggregate shock z_t, the model predicts a relationship between the firm's idiosyncratic productivity s and its volatility. The coefficient of variation of the weighted sum of TFPR to which the firm is exposed, conditional on serving m markets, is

$$CV_t(s) = \frac{\sqrt{Var(\sum_{n=1}^{m} (s z_t p_{n,t})^{1/(1-\alpha)})}}{E(\sum_{n=1}^{m} (s z_t p_{n,t})^{1/(1-\alpha)})}.^{20} \tag{19}$$

Note that equation (19) is presented as the coefficient of variation for a given firm with productivity s. However, an identical expression can be derived if we focus on the coefficient of variation across establishments conditional on firm level productivity. The analysis that follows is consistent with either interpretation.[21] From equation (17), it is evident that the firm will participate in an increasing number of markets as a function of its productivity s. Therefore, the coefficient of variation is a function of the firm's productivity through its effect on the optimal number of markets that the firm will serve. Then, using the optimal market exposure decision, the coefficient of variation for a firm with productivity s can be written as

$$CV_t(s) = \sqrt{\frac{e^{\sigma_\xi^2} - 1}{m_t(s)}}. \tag{20}$$

This result is based on the assumption that the shocks $\xi_{n,t}$ are iid. However, as long as the shocks are not perfectly correlated (which would make them, in fact, one unique shock), the

[19] The next section presents a set of testable implications to connect the model with the empirical evidence.

[20] We also use equation (20) to calibrate the market-specific shocks for firms with exposure to only one market (the KFS firms).

[21] As we discuss in the next section, consistent with the model, the data shows that volatility is countercyclical at both levels of aggregation.

coefficient of variation decreases as the firm is exposed to an increasing number of shocks. This can be seen by analyzing the variance covariance matrix of the shocks $\xi_{n,t}$. Given that they have the same variance, the variance covariance matrix can be rewritten in terms of the correlation coefficient between two shocks multiplied by the common variance term. The coefficient of variation is then given by the following expression for the case of a firm that serves $m_t^*(s)$ markets

$$CV_t(s) = \frac{\sqrt{(e^{\sigma_\xi^2} - 1) \sum_{u=1}^{n} \sum_{v=1}^{n} \rho_{uv}}}{m_t(s)}, \tag{21}$$

where ρ_{uv} is the correlation coefficient between the shocks u and v. In the case of iid shocks the double sum equals the number of shocks, and in the case of perfectly correlated shocks it equals the square of the number of shocks. Anything in between means that the coefficient of variation drops as the number of varieties increases.

A key prediction of the model that can be derived from equation (20) is that for firms that expand in booms and contract in recessions, the coefficient of variation at the firm level is countercyclical. Thus, the model asks us to split the data sample between those firms that adjust the number of markets to which they are exposed and those that do not (as opposed to, for example, splitting the sample by firm size). We perform this critical empirical test in Section 6 and show that the model is consistent with the empirical evidence. Moreover, we also observe that the variance of the weighted sum of TFPR to which the firm is exposed is countercyclical given that the variance of prices follows the term A_t in equation (16), which, at the calibrated parameters, is countercyclical. The fact that A_t is countercyclical implies a countercyclical variance in prices across markets, which is consistent with the evidence provided by Berger and Vavra (2011). Further, under our assumption of one establishment per market, the variance of TFPR at the plant level is countercyclical, as reported by Kehrig (2011).

5 Calibration

This section presents the calibration of the model. Using this calibration we then explore further the workings of the model to then study the business cycle properties of firm-level volatility.

We assume that firm-level productivity is distributed following a log-normal distribution with mean $\bar{s}$ and standard deviation σ_s, so $\log(s) \sim N(\bar{s}, \sigma_s^2)$. The number of markets, N, only determines the scale of the problem. We set its value to 100, but this number is irrelevant for our results. We assume that $z_t \in \{z_B, z_G\}$ with transition probability $\Gamma(z', z)$ and denote by Γ_{kj}, the $(j,k)th$ element of $\Gamma(z', z)$. We normalize $z_G = 1$. This leaves us with ten parameters to calibrate

$$\{\rho, \sigma_\xi, \alpha, \nu, \psi, \bar{s}, \sigma_s, z_B, \Gamma_{GG}, \Gamma_{BB}\}. \tag{22}$$

We calibrate the preference parameter ρ to .83, a standard parameter in the trade literature.[22] We set $\alpha = 0.64$, also a standard value in the literature, that matches the labor share of output. Once we have ρ and α, we use equation (20) to determine σ_ξ. More specifically, we set $\sigma_\xi = 3.04$ to match the standard deviation of $\log(\hat{\epsilon}^{\frac{\rho}{1-\alpha\rho}})$, where $\hat{\epsilon}$ is estimated from our KFS sample using equation (1). This is a good approximation under the assumption that these very small firms are exposed to only one market, and it allows us to pin down the dispersion of market-specific risk. To calibrate Γ_{GG} and Γ_{BB}, we estimate the fraction of booms and recessions with data from the NBER. More specifically, for a given year, we identify a recession indicator to one if two or more quarters in that year were dated as part of a recession by the NBER. Then, we identify years where the indicator equals one with our periods of $z = z_B$ and construct a transition matrix. The estimate of Γ_{kj}, the $(j,k)th$ element of the aggregate state transition matrix, is the ratio of the number of times the economy switched from state j to state k to the number of times the economy was observed to be in state j. We find that Γ_{GG} is 0.86 and that Γ_{BB} is 0.43. This implies that the unconditional probability of z_G and z_B are 0.80 and 0.20 respectively. Finally, we set $z_B = 0.90$. This amplitude of the support for z is in line with the data presented by Gordon (2005), where the average peak-to-trough distance in terms of output gap is 7.9 percent for the period 1945-2005.[23]

The four remaining parameters, $\{\nu, \psi, \bar{s}, \sigma_s\}$, are jointly calibrated so that the average model firm size distribution (in terms of the number of employees) matches the year 2008 firm size distribution from the Census Bureau's Business Dynamics Statistics (BDS).[24] These parameters are the mean and standard deviation of the distribution of productivity (at the firm level) as well as the firm expansion parameters which allow the model to capture the

[22] In a model with monopolistic competition, this would imply a 20% markup. Recall, though, that there is no markup in our model.

[23] This is computed by averaging the peaks and the troughs during the sample and taking their difference. Note that this time period excludes the 2007-2009 recession and the Great Depression, as well as all the previous recessions that had a much stronger impact in terms of GDP.

[24] BDS covers all employer firms (around 5 million) that, in total, employ around 120 million workers. For 2008 we observe 5,186 firms in our Compustat sample, less than 0.1% of the total number of firms.

fat tail in the firm size distribution.[25]

Table 1 describes the main parameters of the model.

Table 1: Model Parameters

Parameter		Value	Target
Preference Paramater	ρ	0.83	Elasticity of Substitution
Dispersion Taste Shock	σ_ξ	3.04	$SD(\log(\hat{\epsilon}^{\frac{\rho}{1-\alpha\rho}}))$ from KFS
Labor Share	α	0.64	Standard Value
Aggregate Prod.	z_G	1	Normalization
Aggregate Prod.	z_B	0.90	Peak to Trough Amplitude
Transition Prob.	Γ_{GG}	0.86	NBER boom/recession
Transition Prob.	Γ_{BB}	0.43	NBER boom/recession
Cost Function	ν	0.56	Firm Size Dist. (see Table 2)
Cost Function	ψ	0.46	Firm Size Dist. (see Table 2)
Mean Productivity	$\bar{s}$	ln(1.7)	Firm Size Dist. (see Table 2)
Std Dev. Productivity	σ_s	0.4	Firm Size Dist. (see Table 2)

The match accuracy for the distribution of employees across firms is shown in Table 2.[26]

Table 2: Firms size distribution - Number of employees

Employment size	Data	Model
Firms with 1 to 4 employees	0.610	0.601
Firms with 5 to 9 employees	0.176	0.209
Firms with 10 to 19 employees	0.107	0.100
Firms with 20 to 99 employees	0.089	0.064
Firms with 100 to 499 employees	0.015	0.021
Firms with 500 employees or more	0.003	0.005

We observe that the model adequately replicates the firm size distribution for all size classes.

[25]To compute the average distribution in the model, we draw 100,000 firms from the idiosyncratic productivity distribution and simulate the model 20 times for 50 periods in each simulation where aggregate shocks are drawn from $\Gamma(z, z')$.

[26]Given that in the model we have a measure of firms equal to one, the model distribution reported was adjusted for the difference in mean.

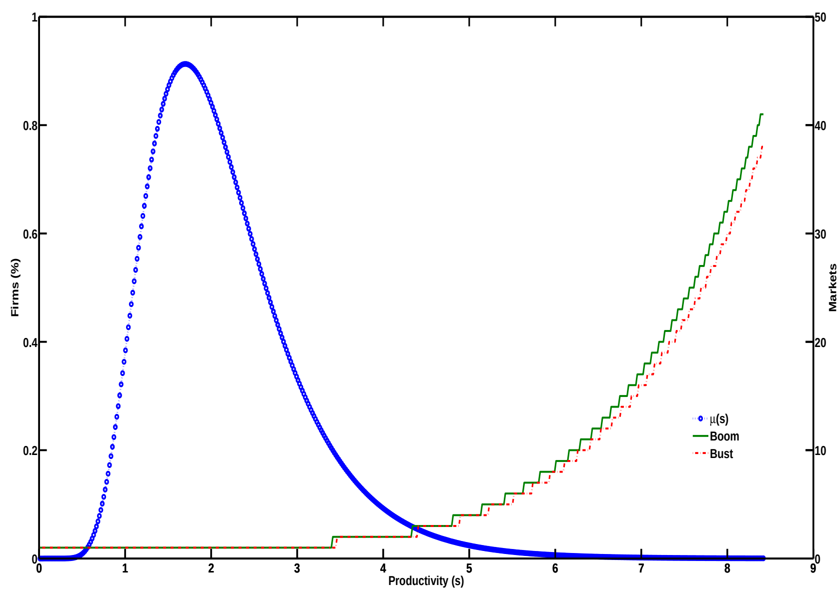
6 Testable Implications of the Model

In this section, we further explore the workings of the model and derive a set of testable implications that we compare with the data in the following section. We start by analyzing how the number of markets, selling expenses, and volatility behave over the business cycle then move to the determinants of firm-level idiosyncratic volatility.

6.1 Business Cycle Implications

Our first step is to examine how a movement in z affects market exposure and the cross-sectional distribution of firms in the model. Figure 4 shows the effect of the aggregate shock on the endogenous number of markets that each firm serves. Changes in z have an asymmetric impact on firm-level decisions. The most productive firms expand in response to an increase in the aggregate shock, whereas the less productive firms change their market exposure only slightly. This cyclical expansion and contraction is in line with the procyclical net entry rate found for the manufacturing sector by Lee and Mukoyama (2012). Moreover, the uneven response of the change in the number of markets by firm size is also consistent with the data (see Figure 6 and Table 6 below).

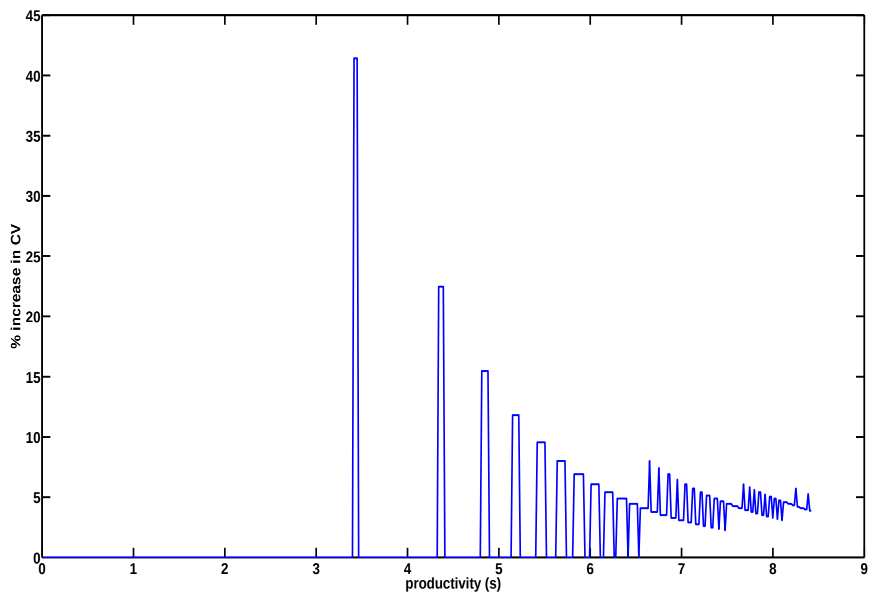
Figure 4: Market Exposure over the Business Cycle



Another testable implication of the model is the cyclical properties of selling expenses and GDP. We find that the model predictions are very much in line with the evidence. In the model, as a result of the contractions and expansions of selling expenses over the business cycle, the labor force that is employed in the production of intangibles accounts for 17.8 percent of the total labor force during boom years and is reduced by 2.65 percent in the low-TFP years. Moreover, the correlation between GDP and median selling expenses for the most productive 5 percent of firms is 1. Sampling from the top of the model's distribution resembles Compustat since Compustat corresponds to the right tail of the firm size distribution. In the data (*i.e.,* Compustat), the correlation between selling expenditures and GDP is 0.283.

Consistent with the characterization of the equilibrium, changes in z generate an endogenous change in firm-level volatility. The impact of changes in z_t on the coefficient of variation from equation (20), by productivity level, is depicted in Figure 5.

Figure 5: Change in Firm Volatility over the Business Cycle



Note: Percent change in the coefficient of variation
when the economy moves from z_G to z_B (see equation (20))

It is clear that the impact of TFP shocks on volatility (the coefficient of variation) is not monotone by productivity level. The average firm-level volatility decreases by 0.023 percent, and the average firm-level volatility for the top 10 and 1 percent of firms falls by

1.4 and 3.9 percent, respectively. This uneven change in volatility is a direct consequence of firms' asymmetric response to variations in z. The fixed cost of expanding to an additional market creates regions of inaction. We observe that those regions of inaction become smaller as productivity increases. Moreover, the impact of the cycle on the coefficient of variation decreases with productivity in the regions where firms adjust the number of markets they operate, since conditional on z high productive firms are better diversified than those with low productivity. From this discussion, we conclude that (a) the idiosyncratic volatility of firms engaged in market expansions and contractions should be countercyclical, and (b) the idiosyncratic volatility of those firms not adjusting should be acyclical. As we show below, this is consistent with the empirical evidence.

In this model with firm heterogeneity, the endogenous variation in the number of markets also has an effect on measured aggregate TFP. As is standard, aggregate measured TFP is computed as aggregate production over aggregate labor (the only input of production) to the power α. In this model, with a unit measure of labor, measured aggregate TFP in period t equals total output $\sum_n^N \sum_s q_{t,n}(s)\lambda_{t,n}(s)$. As z increases and more productive firms expand proportionaly to a larger set of markets, there is an additional positive effect on measured TFP over the change in z. This endogenous amplification effect on measured TFP is non-negligible and amounts to a further 13 percent increase in measured TFP beyond the effect of the aggregate shock z.

Finally, using the pseudo-panel of firms from the model, we estimate firm-level volatility as we did in the data. That is, we compute the log difference in sales from period t to $t+1$ and regress it against a firm fixed effect, size (in terms of number of employees), and a time dummy capturing aggregate conditions (booms or recessions). That is, we estimate

$$\Delta \ln(sales_{it}) = \delta_0 s_i + \delta_1 z_t + \delta_2 \ln(size)_{it} + \epsilon_{it}, \tag{23}$$

and obtain the errors ϵ_{it} from equation (23) to then, as in Castro, Clementi and MacDonald (2009), derive our measure of volatility $\ln(\epsilon_{it}^2)$.[27] Using this measure of risk, we then study its cyclical properties. The findings are summarized on Table 3.

[27]This specification is consistent with the multiplicative heteroscedasticity model analyzed by Harvey (1976).

Table 3: Model Firm-Level Idiosyncratic Volatility over the Business Cycle

	Correlation with Det. GDP	
	All Sample	Top 5%
median $\log(\epsilon_{it}^2)$	-0.421^{***}	-0.200^{*}
Cross-sectional std(ϵ_{it})	-0.179^{*}	-0.345^{***}

Note: *** denotes significant at the 1% level, ** at the 5% level and * at the 10% level. $\ln(\epsilon_{it}^2)$ is constructed from the estimated residual of equation (23).

We find that, when looking at the top 5% of firms from the model (closest to the Compustat sample) as well as when using the entire sample, the measures of firm-level risk are countercyclical—and correlations are significantly different from zero. More specifically, the correlation between median $\log(\epsilon_{it}^2)$ and GDP equals -0.20 (significant at the 10% level), and the correlation between the cross-sectional std(ϵ_{it}) and GDP is -0.345 (significant at the 1% level). These correlations are -0.421 (significant at the 1%) and -0.179 (significant at the 7%) if we compute them using all the firms from the model. In our panel of U.S. firms (i.e. Compustat), as we discussed in Section 2, the correlation between median idiosyncratic risk and GDP is =-0.46 with a 90% interval equal to $[-0.625, -0.257]$; and the correlation between the cross sectional standard deviation of risk and GDP is -0.23 with a 90% interval equal to $[-0.439, -0.017]$.

In summary, the model predicts that low-productivity firms are more volatile than high-productivity firms over the business cycle. Moreover, the model also predicts that the high-productivity firms respond to the changes in aggregate productivity by expanding and contracting to more or fewer markets (with the corresponding change in selling expenses), but these observed changes in market participation do not translate into a monotone relationship in terms of the cyclicality of the volatility as shown in Figure 5. The reason is that high-productivity firms are already exposed to a large number of markets—even in bad times. Therefore, their reaction to aggregate productivity changes does not affect their volatility by much, but the firms that are in relatively few markets in recessions and expand in booms are the ones that experience large changes in their volatility over the cycle.

6.2 Determinants of Firm-Level Volatility

To understand the properties of firm-level volatility and market exposure, we derive a testable implication that links the number of markets $m_t(s)$, selling expenses, and firm-level volatility

$\ln(\epsilon_{it}^2)$ derived from equation (23). The model predicts that market exposure and selling expenses are key to understanding the evolution of firm-level risk. As we describe in detail in the following section, in the data we observe several relatively direct measures of market exposure as well as selling expenses (an indirect measure of market exposure) which in our model correspond to $m^*(s)_t$ and $w_t\Phi(m^*(s))$, respectively. Therefore, we estimate the regression

$$\ln(\epsilon_{it}^2) = \gamma_0 s_i + \gamma_1 \ln(x_{it}) + u_{it}. \tag{24}$$

where $\ln(\epsilon_{it}^2)$ is our measure of firm-level risk, $\gamma_0 s_i$ is a firm fixed effect, and x_{it} represents either the number of markets or selling expenses. Table 4 summarizes our findings.

Table 4: Model Firm-Level Idiosyncratic Volatility and Market Exposure

	Dependent Variable $\ln(\epsilon_{ijt}^2)$			
	All Sample		Top 5%	
$\ln(m_{ijt})$	-0.579	-	-0.210	-
Std Error	0.0034***	-	0.0246***	-
$\ln(expenses_{ijt})$	-	-0.054	-	-0.145
Std Error	-	0.0003***	-	0.0065***

Note: *** denotes significant at the 1% level, ** at the 5% level and * at the 10% level. $\ln(\epsilon_{it}^2)$ is constructed from the estimated residual of equation (23).

The elasticities between firm-level risk and the number of markets and between firm-level risk and selling expenses are -0.579 (significant at 5%) and -0.054 (significant at a 5% level), respectively, when looking at a sample that includes all the firms from our model. Restricting attention to the top 5 percent of firms (which is our model counterpart to the firms included in Compustat) delivers firm-level risk elasticities of -0.210 with respect to markets and -0.145 with respect to expenses. These values are very close to the ones reported in Table 7 (constructed from real-world data).

7 Evidence on Volatility and Market Exposure

In this section, we compare the predictions of the model presented in the previous section with the empirical evidence. We focus on two dimensions in particular: first, we analyze the business cycle dynamics of firm-level risk and measures of market exposure; second, we estimate the relationship between firm-level risk and different measures of market exposure.

We combine several sources to cover many angles of the data.[28] As we discussed in Section 2, we derive our measures of firm-level risk from Compustat and KFS after estimating equation (1). Since the core Compustat sample covers five decades, by focusing on that data set we can analyze how firm-level risk moves over the business cycle. Furthermore, we match our Compustat panel with two other data sets. First, we link Compustat with the Compustat-Segment data. The Segment data provide information on sales for each firm by four-digit SIC industry codes at annual frequency for most years in our sample.[29] Like Bloom, Schankerman and Van Reenen (2013), we use line of business (*i.e.,* SIC codes) information as one of our direct measures of product market exposure.[30] Second, we match Compustat with the U.S. Census Bureau's Longitudinal Business Database (LBD). This considerable task allowed us to obtain information on the number of establishments, as well as their location (at the Metropolitan Statistical Area (MSA) level), for firms in our Compustat sample. The number of establishments and number of MSAs where a firm is operating provide two new measures of market exposure.[31] Finally, we also use the Census Bureau's Business Dynamics Statistics (BDS) data since it is possible to derive the average number of establishments by firm size (employment), year by year starting in 1977, and analyze its cyclical properties.

The first prediction of the model that we test is whether market exposure is procyclical for those firms engaged in market expansions and contractions (*i.e.,* predictions derived from Figure 4). To do so, Figure 6 reports how the average number of markets firms participate in (as measured by four-digit industry codes, number of establishments, number of MSA, and the product of SIC codes and establishments) moves for firms that do change (firms that we define as "Changers"). As predicted by the theory, the average change of the changers behaves procyclically for all our definitions of market participation. The correlation coefficients between detrended GDP and average change in market participation for changing firms is 0.28 for SIC codes, 0.48 for establishments, 0.51 for MSAs, and 0.31 for SICs*establishments

[28] We direct the interested reader to the Appendix for a detailed explanation of how our sample is constructed and the match across data sets is performed.

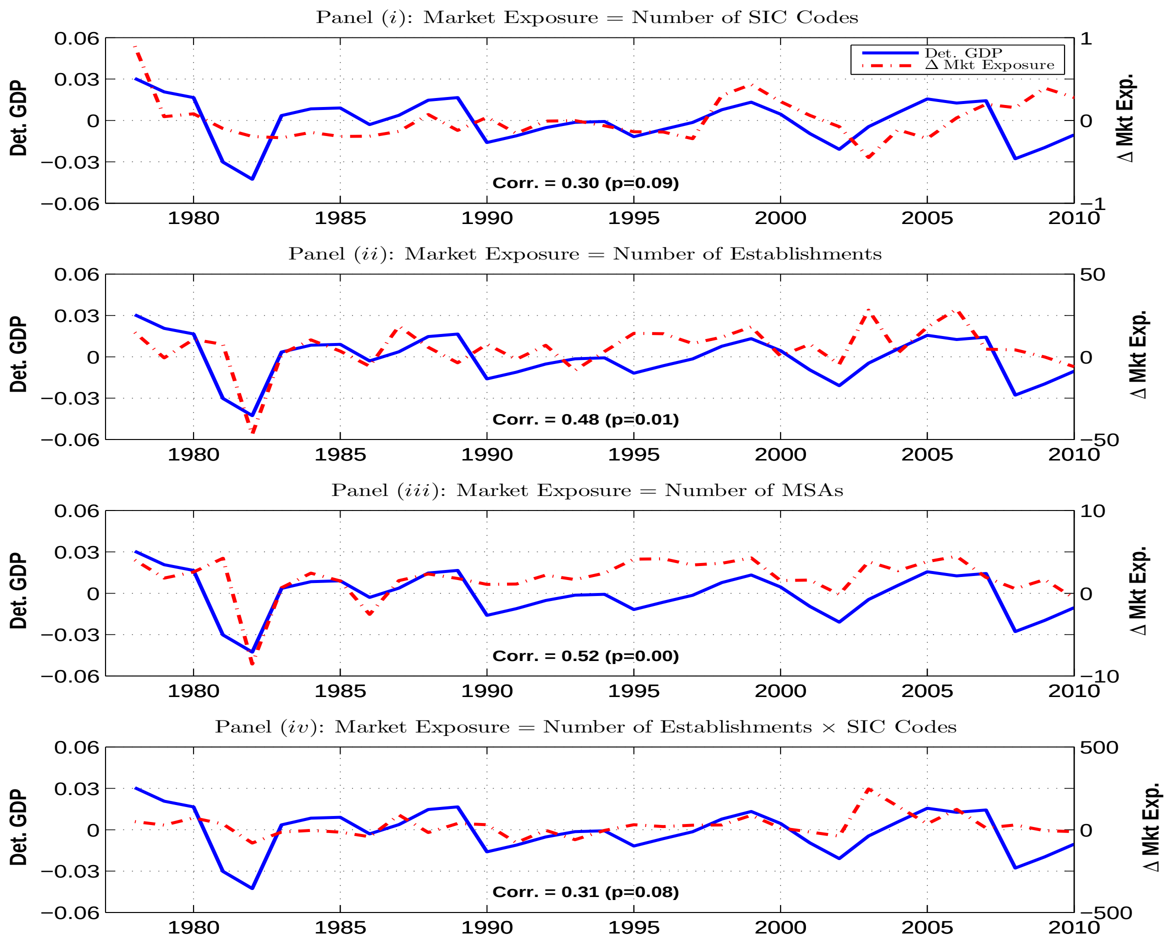
[29] The sample starts in 1977 and provides 183,991 firm/year observations.

[30] On average, each firm reports 2.68 industry codes every year (approximately 5 industry codes per year when weighted by sales).

[31] We understand that these measures of market reach (SIC codes, establishments, and geographical location) have weaknesses. For example, business lines, even at the four-digit level, can be associated with R&D; the construction of a plant has an investment component that we do not consider in the model, and firms in some industries might ship their goods to various locations from only one establishment (this is more problematic in manufacturing than in services or retail). However, the fact that most of our results are robust across market exposure measures is evidence that the mechanism in the model is present in the data.

with respect to detrended GDP.

Figure 6: Avg Change in Market Exposure for "Changers"



Note: Source Compustat-Segment and Compustat-LBD data. Detrended GDP corresponds to detrended log-real GDP. The market exposure measure corresponds to the number of four-digit industry codes (*i.e.,* line of business), number of establishments a firm operates, number of MSAs in which firms have establishments, and the product of establishments and SIC codes. "Changers" refers to firms that change market exposure measure in a given period. We report the average change in the market exposure conditional on being a Changer. GDP is detrended using an H-P filter with parameter 6.25.

Table 5: Descriptive Statistics - Changers vs. Non-Changers

	All Sample		Changers		Non-Changers	
	mean	std dev	mean	std dev	mean	std dev
Number of SIC codes						
Sales	1607.06	8678.85	2739.44	12460.05	1387.62	7716.03
Employment	8.42	33.90	11.72	41.46	7.77	32.19
SGA	268.78	1416.04	464.69	1979.45	230.33	1273.06
Adv	50.12	272.79	80.45	366.67	43.44	246.89
SICs	2.62	1.86	3.32	2.42	2.49	1.69
Number of Establishments						
sales	1553.35	8307.57	2316.25	9547.18	270.52	1827.89
emp	8.33	33.44	12.30	41.20	1.43	8.22
SGA	260.00	1370.46	399.23	1633.71	56.34	331.77
Adv	48.64	264.46	77.22	307.50	9.15	70.88
Establ.	115.85	564.74	215.03	765.37	8.20	77.24
Number of MSAs						
sales	1553.35	8307.57	2582.83	10321.53	417.92	2573.87
emp	8.33	33.44	13.66	44.13	2.26	12.39
SGA	260.00	1370.46	438.54	1724.72	85.78	564.55
Adv	48.64	264.46	85.73	325.79	15.14	111.61
MSAs	32.24	92.75	65.52	127.20	8.13	40.71
Number of SIC * Establishments						
sales	1553.35	8307.57	2108.33	8945.47	253.21	1840.32
emp	8.33	33.44	11.39	39.10	1.36	7.92
SGA	260.00	1370.46	363.59	1543.83	53.31	330.83
Adv	48.64	264.46	70.89	289.98	8.99	73.45
SIC*Establ	405.99	2552.05	704.83	3388.15	22.38	427.74

Note: Source: Compustat-Segment and Compustat-LBD databases. Sales; Sales, General and Administrative expenses (SGA); and Advertising Expenses (Adv) are expressed in millions of dollars deflated using BEA 2-digit SIC price deflators for value added. Employment (Empl) is expressed in thousands of employees.

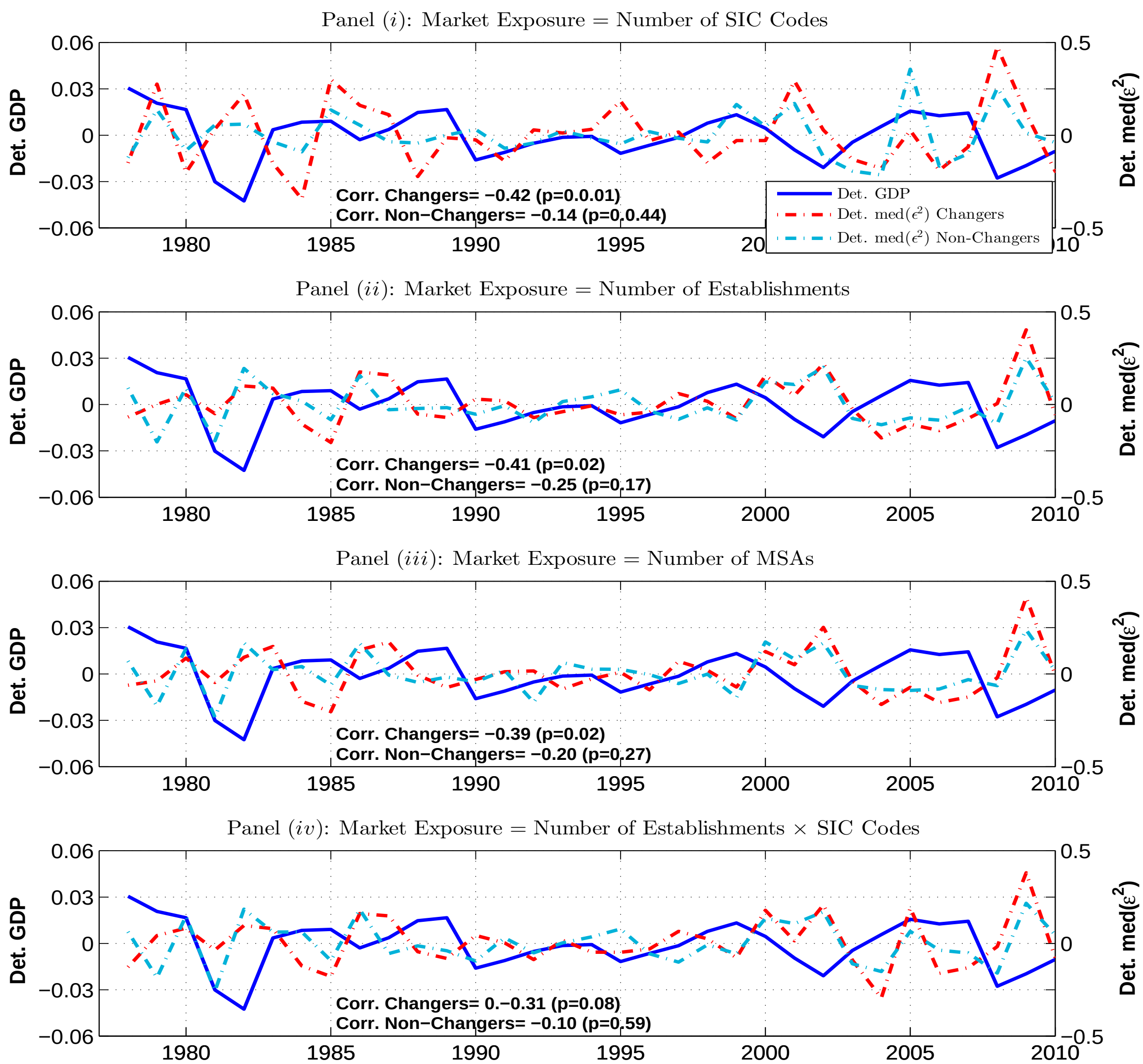
An implication of the model is that firms that react to the cycle by changing the number of markets in which they participate are larger on average than those that do not change their market exposure. Table 5 shows descriptive statistics for the whole Compustat-Segment database and Compustat-LBD database, for the changers and non-changers groups. Also, consistent with the implications described on Figure 4, we find that the fraction of firms that do change their market participation is acyclical.[32]

We find that, when we condition on the number of SIC codes, the changers are around twice as big as the non-changers in terms of sales, SGA expenses, and advertising expenses. They are 50 percent larger in terms of employees and 33 percent larger in terms of the number of products they offer (measured by the number of SIC codes for which they report sales). But the changers are between 5 and 9 times larger than non-changers when we condition on the number of establishments each firm operates or the number of MSAs in which each firm is present and look at sales, employees, or expenditures. Changers are 26 times larger than non-changers in terms of the number of establishments, and 31 times larger in terms of the product of SIC codes and establishments.

The next implication of the model that we test is whether, by reacting to the business cycle, firms that change their market exposure experience a countercyclical pattern of volatility, whereas the firms that do not change their market exposure have an acyclical pattern (*i.e.,* we find evidence of the non-monotone relationship depicted in Figure 5). We find that the data are consistent with the predictions of the model. Once we split the sample into "Changers" and "Non-changers" (using our four different definitions of markets) we see that the correlation of median ϵ^2 and GDP for "Changers" and "Non-changers" is different. Exactly as predicted by the model, in each of the market definitions, the "Changers", median ϵ^2 is countercyclical, with a correlation between -0.31 and -0.422 (significant at the 5% level) with respect to GDP. On the other hand, the correlation of the median ϵ^2 and GDP in the case of the "Non-changers" is between -0.098 and -0.247 and is not significantly different from zero in all cases. Figure 7 shows the cyclical behavior for "Changers" and "Non-Changers" as described above.

[32]Market participation is measured by the number of products or SIC codes for which they report sales, the number of establishments they operate, the number of MSAs in which they have a presence, or the product of establishments and SIC codes. The fraction of changing firms accounts for 20, 52, 42, and 56 percent of the total number of firms, respectively, and this fraction is uncorrelated with GDP

Figure 7: Volatility of changers vs. non-changers



Note: Source Compustat-Segment and Compustat-LBD data. Detrended GDP corresponds to detrended log-real GDP. The market exposure measure corresponds to the number of four-digit industry codes (*i.e.,* line of business), number of establishments a firm operates, number of MSAs in which the firms are present, and the product of establishments times SIC codes. “Changers” refers to firms that change market exposure measure in a given period. “Changers” refers to firms that experience a change in their market exposure measure. “Non-changers” refers to firms that do not change their market exposure measure. All series are detrended using an H-P filter with parameter 6.25.

So far we have shown that, conditioning by changers and non-changers, the predictions of the model hold. Now we condition on size and find not only that the changers are big, but also that large firms tend to be changers. We focus on the number of active establishments by firm. Using the publicly available Business Dynamics Statistics (BDS) data set it is possible to derive the average number of establishments by firm size (employment), year by year from 1977 to 2009, and analyze its cyclical properties.[33] The last three columns of Table 6 present evidence on the change in the number of establishments (plants) by firm size between periods when log-real GDP is above and below trend as well as the correlation of the number of establishments per firm with GDP (conditional on firm size).

This table shows that, for most size categories, there is a minimal change in the number of establishments per firm between periods when GDP is above trend and those when it is below (the correlation with det. GDP presents similar results). However, for large firms (those with with at least 5000 workers) the number of plants is larger when GDP is above trend than when GDP is below trend, and the elasticity with detrended GDP is close to 1. This difference is economically and statistically significant.[34] This is relevant in terms of activity and observed dispersion because, as Table 6 shows, these firms account for about 30 percent of total employment and represent the 1,450 largest firms in the economy (just under half of the number of firms included in our Compustat sample)[35]. Furthermore, since the change in the number of plants is approximately 8 between periods when GDP is above trend vs periods when GDP is below trend in these 1,450 firms, and these firms employ around 75 workers per plant, the change in employment coming only from this margin amounts to 1.29 percent of total private non-farm employment.[36]

[33] The Business Dynamics Statistics (BDS) data are compiled from the Longitudinal Business Database (LBD). The LBD is a longitudinal database of business establishments and firms covering the years from 1977 on. The BDS series provide annual statistics by firm size on the number of establishments as well as gross job flows for the entire economy.

[34] This is consistent with the evidence presented in Moscarini and Postel-Vinay (2012) that the net job creation of large firms or establishments comoves negatively and more strongly with aggregate unemployment than the net job creation of small employers at business cycle frequencies.

[35] Note that the reported numbers in Table 6 correspond to detrended averages from the period 1977-2009. The total number of firms for the year 2009 was around 3,000.

[36] Another margin of adjustment for firms is the number of workers per plant. As we show in Table 19 in the Appendix, the variation in the average number of workers per establishment is positive and significant for small firms but not for large firms. Moreover, the change in the number of workers over the business cycle coming from the change in the number of plants per firm is larger than the change in the number of workers coming from adjustments in the number of workers per plant (which represents 1.15 percent of total private non-farm employment).

Table 6: Number of Plants per Firm over the Business Cycle

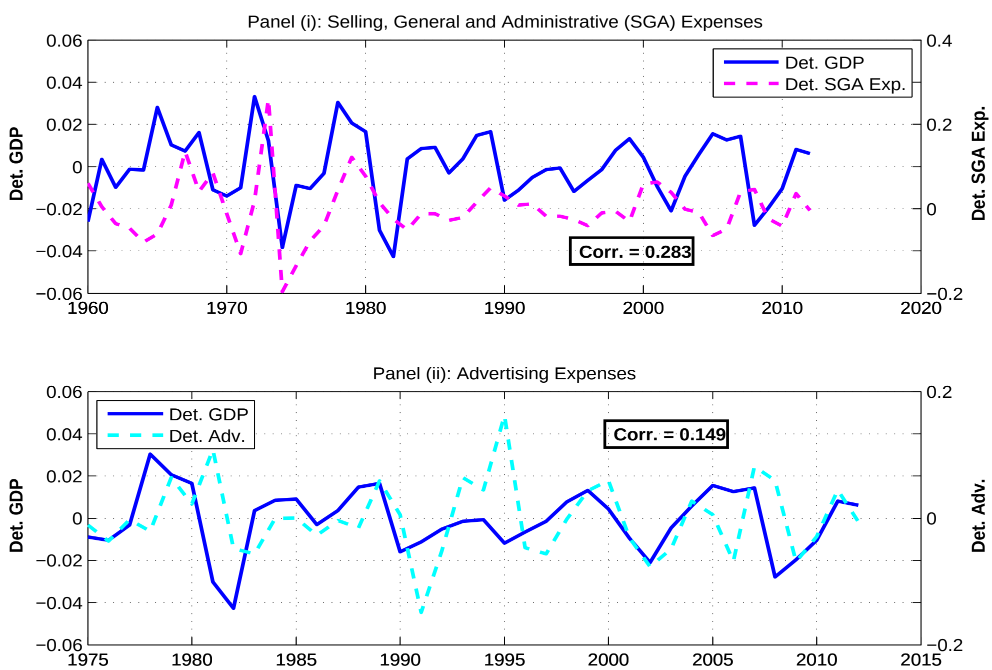
Firm Size (# workers)	Avg. # of Firms (in 1000's)	Fraction Total Emp. (%)	Avg. Emp. per Plant	Cyclical Prop. # Plants per Firm		
				Avg. # Plants when GDP		Elast. w/ GDP
				below trend	above trend	
1 to 4	1908.71	6.55	2.31	1.00	1.00	-0.009
5 to 9	736.37	7.32	6.59	1.03	1.03	-0.018
10 to 19	407.70	8.40	12.68	1.10	1.09	0.048
20 to 49	237.02	11.01	24.43	1.28	1.27	0.151
50 to 99	71.04	7.54	40.23	1.77	1.73	0.023
100 to 249	35.00	8.20	51.44	3.02	2.95	-0.436
250 to 499	9.77	5.16	59.00	5.85	5.74	-0.194
500 to 999	4.68	4.81	63.17	10.54	10.63	0.179
1000 to 2499	3.04	6.52	66.13	21.56	21.28	-0.096
2500 to 4999	1.11	4.77	60.53	46.69	46.77	0.378
5000 +	1.45	29.74	75.81	167.43	175.19	0.953*

Note: The source is U.S. Census Bureau, Business Dynamics Statistics (BDS) Data Tables. We extract a linear trend component to all variables. The "Avg. # of Firms" corresponds to the average number of firms in each size bin over our sample (in thousands). "Fraction Total Emp." is computed as the average of total employees in each size bin divided by total employment. "Avg. Emp. per Plant" corresponds to the average of the number of employees per establishment in each size category. "Avg. Number of Plants when GDP is below or above trend" is derived from a linear regression of the average number of establishments by firm size on a constant, a linear trend and a dummy that identifies periods where GDP is above trend. GDP corresponds to log-real GDP. The trend for GDP is computed using the H-P filter with parameter 6.25. "Corr. w/ GDP" corresponds to the correlation between the average number of plants and detrended GDP. This correlation is derived from a linear regression of log average number of establishments by firm size on a constant, a linear trend and log real detrended GDP. * denotes significant at the 10%.

Also, within-firm expansions and contractions seem to be correlated with the cycle. Broda and Weinstein (2010) report that the product portfolio of firms is procyclical, where the product count is based on the "bar codes" a firm uses. This measure is consistent with our evidence and our model. In bad times, firms contract their product mix; in good times, firms expand their product mix and expose themselves to more markets.

While not as direct as the measures of market exposure presented so far, guided by our model, we also look at how expenses associated with market reach move with the business cycle. In the model, the cost of market exposure is given by $w_t \Phi_t(m)$ and is predicted to be procyclical given that it is a function of m. In Compustat we look at Selling, General and Administrative (SGA) expenditures as the measure associated with running the firm and a function of its complexity. We also look at the advertising component within SGA expenditures, as it should follow closely the market reach of the firm. Figure 8 shows the correlation between our indirect measures of market exposure and GDP.

Figure 8: Market Reach Expenses and Business Cycles



Note: Compustat sample. Real log (SGA and Advertising) expenses correspond to the median of the observed distribution in any given year. Real log GDP from FRED Economic Data (St. Louis Federal Reserve Bank). Series are detrended using H-P filter with parameter 6.25. GDP data are available since 1947. In Panel (i), expenses are measured Selling, General and Administrative expenses. In Panel (ii), log real expenses are measured are measured by Advertising Expenses.

This figure shows that log real GDP and our measures of market reach expenses are positively correlated. The correlation is 0.283 (significant at the 5% level) and 0.149 (significant at the 10% level) when expenses are measured as Selling, General and Administrative expenses and Advertising, respectively.

7.1 Determinants of Firm-Level Volatility

We now turn our attention to the determinants of firm-level volatility. With our estimate of idiosyncratic risk ϵ_{ijt} from equation (1), as in Clementi, Castro and MacDonald (2009), we proxy its variance at the firm level by $\ln(\epsilon_{ijt}^2)$ and study how it is related to our different market exposure measures once industry-specific factors are accounted for.[37] In particular, we estimate the following log-linear equation (as we do for the model):

$$\ln(\epsilon_{ijt}^2) = \gamma_i + \theta_{tj} + \alpha_1 \ln(X_{ijt}) + \alpha_2 t + u_{ijt}, \tag{25}$$

where γ_i is a firm fixed effect, θ_{tj} is an industry- and year-specific component, $\ln(X_{ijt})$ is the measure of market exposure for firm i in sector j at time t, and t is a time trend.[38] We use many different market exposure measures as our X_{ijt} from different sources. We use Compustat linked to the LBD to obtain the number of establishments each firm operates at each point in time. Also, given that we have the location of the establishment, we can identify the number of Metropolitan Statistical Areas (MSA) in which a firm is operating at each point in time. Using the segment data in Compustat we also look at the number of SIC codes for which a firm reports sales in a given year as a measure of product market exposure. We also look at the interaction between geographic locations (establishments) and product markets. Finally, we consider indirect measures of market exposure such as Sales, General and Administrative (SGA) expenses and Advertising expenses in Compustat and SGA in KFS for the case of the small firms.[39]

Table 7 reports the results of a selected number of regressions.

[37] This specification for the variance allows us to identify a value for the variance for every firm in industry j and year t, and it is consistent with the multiplicative heteroscedasticity model analyzed by Harvey (1976). More specifically, this formulation results from assuming that σ_{ijt}^2, the variance of the disturbance in equation (1) (*i.e.,* the variance of ϵ_{ijt}), takes the following form: $\sigma_{ijt}^2 = \exp(\gamma_i + \theta_{tj} + \alpha_1 \ln(X_{ijt}) + \alpha_2 t)$.

[38] We will show below that, consistent with the evidence presented in Comin and Phillipon (2005), a time trend is necessary because the variance of idiosyncratic risk for public firms has been rising during the last 30 years.

[39] We perform a large set of robustness checks that are reported in the appendix.

Table 7: Dependent variable $\ln(\epsilon_{ijt}^2)$

X	Estabs	MSAs	SICs	Est*SIC	Adv	SGA	SGA
$ln(X)$	-0.081	-0.094	-0.137	-0.075	-0.134	-0.301	-0.085
S E	0.0088	0.0102	0.0212	0.0080	0.012	0.009	0.036
N	129724	129724	155175	124433	66962	177178	2547
R^2	0.0180	0.0180	0.0178	0.0183	0.0423	0.0435	0.16
Source	LBD	LBD	Comp	LBD	Comp	Comp	KFS

Number of establishments and MSAs taken from the LBD, Number of SICs from Compustat segment database. All results are significant at 1% level other than KFS, which is significant at 5%. All regressions include firm fixed effects, industry-year controls, and time trends

The results are very close in terms of magnitudes for the regressions that use establishments, MSAs, SIC codes, and their interaction. The elasticity of firm-level volatility and these measures is between 7.5 and 13.7 percent. Even using advertising expenses as the measure for market reach delivers an estimate that is very close to those obtained using direct measures of market reach. All of the measures reported in the first five regressions use either Compustat or our Compustat-LBD link, so the model counterpart for these firms must be the top end of the firm size distribution. In the model, when we look at the top 5 percent of firms by productivity, the elasticity of risk to market exposure is -0.21—which is close to the numbers reported above.

Finally, when looking at the indirect measures of market exposure, namely SGA expenditures, we find that by restricting to Compustat firms the elasticity is -0.3 and the same number changes to -0.085 on the other end of the firm size distribution. In this dimension the model also performs well. It delivers an elasticity of -0.14 when we restrict the attention to the top 5 percent of firms, and the elasticity changes to -0.05 if we consider the universe of firms.

8 Conclusion

Consistent with previous literature, using a panel of U.S. firms (Compustat) we document the countercyclical nature of idiosyncratic firm-level volatility. We propose a theory of endogenous volatility over the business cycle based on firm-level market exposure to explain this fact. In our model, firms pay a cost to be able to expand to a larger number of markets. The result is that high-productivity firms expand to a larger set of markets, making them less volatile than their low-productivity counterparts. Importantly, low-productivity firms do not react to the cycle, whereas medium scale and large firms do, explaining the cyclical properties of firm-level volatility.

From the model, we derive a set of testable implications for measures of market exposure and firm-level volatility to then show that the empirical evidence is broadly consistent with the theory. Specifically, using data from Compustat, segment data, and the BDS, we show that measures of market exposure (both direct measures such as line of business, establishments, or their geographical location and indirect measures such as selling expenses and advertisement) are procyclical and that the volatility of firms that expand and contract is countercyclical (as opposed to acyclical for those not engaged in market expansions and contractions). Moreover, using Compustat, the LBD, and KFS, we show that firm-level idiosyncratic risk is negatively correlated with all measures of market exposure (even after controlling for firm, year, and industry fixed effects).

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A1 Appendix

A1.1 Kauffman Firm Survey Sample

The Kauffman Firm Survey (KFS) is a large panel of "young" businesses. Firms in the sample were founded in 2004 and have been tracked annually.[40] This panel was created using a random sample from Dun and Bradstreet's database list of new businesses. The target population consists of all new businesses that were started in the 2004 calendar year in the United States, and it excludes any branch or subsidiary owned by an existing business or a business inherited from someone else. The sample for the first survey consisted of 4,928 businesses.

The KFS provides us with the unique opportunity to study a panel of new businesses from startup, using available data on their revenues and expenses, the number of workers, the products, services, and innovations that these business possess and develop in their early years of existence, and the extent to which these business are involved in innovative activities. One drawback of the publicly available KFS data is that some variables, such as assets (and its components) and sales, are only reported within certain ranges.[41] We set the value of the corresponding variables to the middle value of the reported range.[42]

Our unit of observation is the firm, as defined by the KFS. The change in sales is constructed from total revenues from sales of goods, services, or intellectual properties. Size, as is standard in the literature, is defined as the number of employees. We use two-digit NAICS codes to control for industry effects. All variables are deflated using two-digit industry deflators. Expenses is defined as expenses that do not correspond to production inputs. It is constructed as total expenses in selling and general expenses (SGA) that include expenses in, for example, design of new products, brand development, advertising, marketing, organizational development, or management consulting. For firm/year observations with missing values of SGA expenses, we compute the average ratio of SGA expenses to total expenses and input SGA expenses from this ratio and total expenses.

Table 8 presents the distribution of real sales and real SGA expenses for newborn firms (*i.e.,* the distribution of firms in 2004) and for firms that survive until the end of our sample (2008).

[40] Current available data extend through year 2008. Firms will continue to be tracked through 2011. See http://www.kauffman.org/kfs/ for a detailed description of the data and the public-use microdata itself.

[41] For example, ranges for revenues are 0, $1-1000, $1001-5000, $5001-10000, $10001-25000, $25001-100000, and $100000 or more.

[42] The set of variables that we use which present this problem are: revenue from sales of goods, services, or intellectual properties, expenses, wages, and assets (and its components).

Table 8: Distribution of Sales and Expenses (%)

	Year 2004		Year 2008	
Thousands of \$	Sales	SGA	Sales	SGA
\$ 0 − 3	14.52	55.09	6.80	37.87
\$ 3 − 10	14.39	26.40	8.71	28.02
\$ 10 − 50	14.59	0.00	8.81	13.83
\$ 50 − 100	28.58	16.64	22.27	15.21
\$ > 100	27.92	1.87	53.40	5.07
# Firms	3,037	4,382	1,940	1,381

Note: Data from KFS. Sales and Exp. SGA expenses are deflated using the GDP deflator.

Observe that many firms are relatively small, with sales and selling expenses below \$10,000. This is still the case even after four years of existence. However, a non-trivial number of new firms have sales and SGA above \$100,000. The distributions clearly shift upwards as the cohort of firms becomes older and grows and as selection takes place.

Table 9 reports the distribution of newly created firms as seen in the KFS, a comparison with the size distribution of new firms from Census data, and the distribution of firms over employment for our cohort of firms in 2008.[43]

Table 9: Distribution of workers (%)

Number of Employees	KFS (2004)	Census (2004)	KFS (2008)
1−4	74.4	76.7	64.8
5−9	15.3	13.0	17.8
10−19	6.6	6.0	9.5
20−99	3.4	3.8	2.9
100−499	0.3	0.4	5.0
500 +	0.0	0.0	0.0

Note: KFS refers to Kauffman Firm Survey. Census corresponds to Office of Advocacy, Small Business Administration, Statistics of U.S. Business, U.S. Census 2004.

Table (9) shows that a large fraction of firms start with only a few workers. More than 70 percent of new firms hire between one and four workers. As a comparison, we report the distribution of new firms from Census data; note that the distributions are very similar. This

[43] For comparison, we report the distribution conditional on firms having more than one worker. In the KFS, we find that in 2004, 58 percent of active firms hire zero workers; this value equals 44 percent in 2008.

reassures us that we have a representative sample of new firms, despite some differences in the distribution of new firms across industries and the different methodologies used across sources. Finally, and consistent with the evidence presented in Table (8), among active firms in the KFS in 2008, there is a sizable reduction in the fraction of firms with less than four workers and an increase in the fraction of firms with more than ten workers.

Table (10) displays the distribution of firms across some representative industries and their one year survival rates.

Table 10: Distribution of firms across industries and survival rates

Industry	Fraction of Firms (%)	One Year Survival Rate (%)
Construction	10.0	91.9
Manufacturing	7.1	92.0
Wholesale	5.4	88.7
Retail	15.9	86.1
Transportation and Warehousing	3.4	84.7
Information	2.7	84.6
Finance and Insurance	4.7	95.8
Administration and Support	9.6	91.7
Accommodation and Food Services	4.3	77.7

Source: Kauffman Firm Survey.

A1.2 Compustat and Compustat-Segment Sample

We use Compustat's fundamental and segments annual data.[44] Our choice of firm identifier is GVKEY, and this is the variable we use for matching the Compustat segment file to the fundamentals file. The sample period for the fundamentals data ranges from 1960 to 2012, but segments data exist only from 1977 to 2012. Not all firms have segment data. Our year variable is extracted from the variable DATADATE (for both the fundamentals and the segments files). We exclude financial firms with standard industrial classification (SIC) codes between 6000 and 6999, utility firms with SIC codes between 4900 and 4999, and firms with SIC codes greater than 9000 (residual categories). Observations are deleted if they do not have a positive book value of assets or if gross capital stock or sales are either zero, negative, or missing. The final sample is an unbalanced panel with more than 21,600 firms

[44] All variable names correspond to the Wharton Research Data Services (WRDS) version of Compustat.

and 241,000 firm/year observations; of these, there are 18,700 firms and 184,000 firm/year observations with segment data.

Our data variables are defined as follows. The change in sales is constructed from the variable SALE. As is standard in the literature, firm size is defined as the number of employees, using the variable EMP. We use two-digit NAICS codes to control for industry effects. Firm age is proxied by the number of years since the firm's first-year observation in Compustat. All nominal variables are deflated using the BEAs two-digit, sector-specific price deflator for value added.

Segment counts reflect the sum of primary and secondary four-digit SIC codes reported in the Compustat variables SICS1 and SICS2. Compustat reports four-digit SIC codes for segments throughout the time sample. NAICS codes are reported also in later years; there are no observations in which a NAICS code is reported but a SIC code is not. BEA deflators for value added are only given for SIC codes until 1998; at that time, BEA began reporting deflators for NAICS codes. Therefore, when possible we deflate segment-level sales using ten sector-level SIC code deflators; elsewhere we deflate with 24 two-digit NAICS sector codes. Thus, our SIC deflators reflect lower industry detail than our NAICS deflators due to the lack of one-to-one mapping between NAICS and SIC; for this reason, we verified that our results are robust to using SIC deflators at the next possible level of detail, for which there are more than 80 SIC codes. For our reported results, we used the sector-level SIC deflators.

Table 11 reports the distribution of real sales and real SGA expenses for firms in 1980 and 2008.[45]

Table 11: Distribution of Sales and Expenses (%)

	Year 1980		Year 2008	
In millions of $	Sales	SGA	Sales	SGA
$ < 10	19.71	27.73	12.44	21.70
$ 10 − 20	9.39	12.41	5.27	12.74
$ 20 − 50	13.99	16.80	10.29	16.85
$ 50 − 100	11.79	11.98	10.10	13.14
$ 100 − 250	14.32	12.94	13.78	13.65
$ > 250	30.8	18.14	48.13	21.92
# Firms	4,581	4,150	5,219	4,741

Note: Data from Compustat. Sales and Expenses are deflated using BEA two-digit SIC price deflators for value added.

[45] Our data extends to 2012, but we present the year 2008 to allow a comparison with the last year of our KFS sample.

Note that firms' sales and selling and general expenses are considerably larger than those in the KFS sample.

Table (12) reports the distribution of employment size for 1980 and 2008. To simplify the comparison, the size bins are the same as the ones we used for the KFS sample.

Table 12: Distribution of workers (%)

	All firms		Segment firms	
Number of Employees	1980	2008	1980	2008
1 − 4	1.64	1.38	1.68	1.38
5 − 9	1.75	1.80	1.77	1.75
10 − 19	2.49	3.14	2.51	2.79
20 − 99	11.07	13.26	11.30	12.49
100 − 499	23.31	21.63	23.50	20.62
500 +	59.75	58.79	59.25	60.97
# Firms	4,581	5,219	4,469	4,627

Note: Data from Compustat.

Most firms in the Compustat sample have more than 500 workers, whereas in the KFS sample this value is less than 1 percent. Table (13) reports the distribution of firm age (computed as the number of years in the sample).

Table 13: Age Distribution (%)

	All firms		Segment firms	
Firm's Age	1980	2008	1980	2008
1 − 5	18.05	26.38	18.12	20.90
6 − 10	41.06	18.85	41.64	19.23
11 − 15	15.06	17.34	15.10	18.63
16 − 20	10.43	10.92	9.85	12.08
21 − 25	0.00	7.86	0.00	8.64
26 +	0.00	14.60	0.00	15.97
Top Censored	15.39	4.04	15.28	4.54
# Firms	4,581	5,219	4,469	4,627

Note: Data from Compustat. Top Censored corresponds to firms that are in our sample starting in 1960.

We employed the following rules when constructing the Compustat dataset. When multiple data source dates (SRCDATE) existed for one firm/data date/segment combination, we kept only the most recent source date. When multiple data dates existed for one firm-year-segment combination, we kept only the later data date unless its sales figure was missing (in which case we kept the earlier data date). When multiple segment identifiers existed for one four-digit SIC code, we combined the segments: segment counts reflect the number of unique four-digit SIC codes, and segment-level employment reflects the sum of all reported segments within a four-digit SIC code.

Finally, table 14 shows the correlations between the variables used from the Compustat-Segment database.

Table 14: Correlations Table - Compustat Segment

	Sales	Empl	SGA	Adv	SICs
All Sample - Compustat Segment					
Sales	1				
Empl	0.7974	1			
SGA	0.8927	0.7486	1		
Adv	0.641	0.4838	0.7162	1	
SICs	0.227	0.2331	0.2284	0.2258	1
Changers					
Sales	1				
Empl	0.7888	1			
SGA	0.8736	0.728	1		
Adv	0.6993	0.533	0.764	1	
SICs	0.205	0.2402	0.1993	0.206	1
Non-Changers					
Sales	1				
Empl	0.7994	1			
SGA	0.8976	0.7531	1		
Adv	0.6243	0.4702	0.7028	1	
SICs	0.229	0.2267	0.2313	0.2275	1

Note: Data from Compustat-Segment dataset. All nominal variables are deflated using the BEAs two-digit, sector-specific price deflator for value added.

A1.3 LBD-Compustat Link

The Longitudinal Business Database (LBD) is constructed from the business register of the U.S. Bureau of the Census (see Jarmin and Miranda (2002)). It includes all nonfarm private sector employer establishments and firms in the United States from 1976 to 2011 and provides information on location, industry, and employment. Employment information reflects the status of establishments as of March 12 of a given year. The LBD links establishments as firms; firm identifiers reflect operational control and can span across state lines.

Both Compustat and the LBD include various firm identifiers that can be used for matching: employer identification numbers (EINs), two alternative business names (in Compustat, these are given by CONM and CONML), and addresses. We obtained further match flexibility by employing the SAS DQMATCH system. We linked Compustat to the LBD using successive "passes" that matched firms using these identifiers with varying degrees of specificity.[46] Early match passes relied on EINs and full business names and addresses (which have been standardized). Subsequent passes utilized algorithms that evaluate name similarity conditional on geographic matches. Final passes employed DQMATCH descriptors. We utilize both alternative name variables from each dataset, thus allowing for potential matches along any combination of name variables. Only residual non-matched CUSIPs are retained after each pass; by ordering passes such that more specific match criteria are tested earlier, we ensure that the final linked dataset is based on the highest possible match quality for each firm.

We eliminate firm-year matches that are out of scope for Compustat activity (as determined by IPODATE and DLDTE when available or by time periods of positive employment, sales, or share price when the former variables are missing). Instances in which a CUSIP was paired with multiple LBD firms were resolved by first dropping LBD firms with only one operating unit then choosing the LBD firm with reported employment closest to Compustat reported employment. Since many firms have time series gaps in EIN coverage, and since business names in the LBD refer to establishments rather than firms and occasionally change over time, we make additional matches by rolling firm-year matches across years when appropriate.

We find matches for about 80 percent of relevant Compustat CUSIPs in the LBD source data; on average, we have about 4,200 observations with relevant nonmissing data per year in our LBD-Compustat Link spanning the years 1977 to 2011. The resulting comingled dataset includes sales and industry data from Compustat with employment and geographic data from the LBD. In the LBD, an establishment is a single business location with one or more

[46]For matching purposes, we first discard from Compustat all exchange traded funds (ETFs) that can be easily identified, American depositary receipts (ADRs) and American depositary shares (ADSs), CUSIPs with non-U.S. geographical identifiers, and firms that operate only outside of North America (as identified by IDBFLAG).

employees. We classify establishment locations using the Census Bureau's 2009 definitions of Metropolitan Statistical Areas (MSA), which are comprised of entire counties (*i.e.,* an MSA is a group of counties). For our estimation purposes, any county that is not included in an MSA is classified as its own MSA.[47]

Table 15: Summary Statistics for LBD variables

	Mean	Std Dev.	Corr. with SGA exp.
Number of estabs	124.67	617.30	0.35
Number of MSAs	34.21	99.14	0.34

Finally, tables 16, 17, and 18 show the correlations between the variables used from the Compustat-LBD database for the different market definitions.

[47]An alternative to this classification is to collect all counties within a state that are not included in an MSA and define that collection as an MSA, so each state has a single residual "MSA" in addition to proper MSAs. We also performed our analyses on data constructed with this definition, but it did not substantially alter the results.

Table 16: Correlations Table - Compustat-LBD: Number of Establishments

	Sales	Empl	SGA	Adv	Establ
			All Sample		
Sales	1				
Empl	0.8	1			
SGA	0.8828	0.7494	1		
Adv	0.656	0.4616	0.7266	1	
Establ	0.3475	0.4483	0.37	0.2301	1
			Non-Changers		
Sales	1				
Empl	0.8365	1			
SGA	0.8638	0.6635	1		
Adv	0.6962	0.5647	0.7872	1	
Establ	0.4473	0.2846	0.5497	0.3556	1
			Changers		
Sales	1				
Empl	0.7927	1			
SGA	0.8807	0.7431	1		
Adv	0.6551	0.4498	0.7265	1	
Establ	0.326	0.4393	0.345	0.2079	1

Note: Data from Compustat-LBD dataset. All nominal variables are deflated using the BEAs two-digit, sector-specific price deflator for value added.

Table 17: Correlations Table - Compustat-LBD: Number of MSAs

	Sales	Empl	SGA	Adv	MSA
			All Sample		
Sales	1				
Empl	0.8	1			
SGA	0.8828	0.7494	1		
Adv	0.656	0.4616	0.7266	1	
MSA	0.3674	0.4788	0.3847	0.2368	1
			Non-Changers		
Sales	1				
Empl	0.8009	1			
SGA	0.8745	0.6527	1		
Adv	0.6802	0.4865	0.7661	1	
MSA	0.3673	0.4098	0.3601	0.2304	1
			Changers		
Sales	1				
Empl	0.7931	1			
SGA	0.8819	0.7491	1		
Adv	0.6562	0.4508	0.7239	1	
MSA	0.3411	0.4619	0.3577	0.2032	1

Note: Data from Compustat-LBD dataset. All nominal variables are deflated using the BEAs two-digit, sector-specific price deflator for value added.

Table 18: Correlations Table - Compustat-LBD: Establishments * SICs

	Sales	Empl	SGA	Adv	Est*SIC
All Sample					
Sales	1				
Empl	0.8024	1			
SGA	0.8837	0.7476	1		
Adv	0.6578	0.4652	0.7274	1	
Est*SIC	0.381	0.4444	0.391	0.2577	1
Non-Changers					
Sales	1				
Empl	0.8386	1			
SGA	0.8553	0.6367	1		
Adv	0.7008	0.5772	0.8003	1	
Est*SIC	0.4896	0.2524	0.6153	0.3827	1
Changers					
Sales	1				
Empl	0.7975	1			
SGA	0.8821	0.7401	1		
Adv	0.6642	0.4614	0.7315	1	
Est*SIC	0.3615	0.4448	0.3625	0.2409	1

Note: Data from Compustat-LBD dataset. All nominal variables are deflated using the BEAs two-digit, sector-specific price deflator for value added.

All reported statisics based on the LBD-Compustat link were reviewed and do not disclose confidential information.

A1.4 BDS Sample

Table 19 presents the cyclical properties of workers per establishment computed from BDS data. Since most variables in this sample have a trend component, we detrended them using a linear trend when reporting the averages in Tables 6 and 19. Table 20 reports the detrended and the non-detrended average (i.e. a simple average) for the variables of interest.

Table 19: Number of Workers per Establishment over the Business Cycle

Firm Size (# workers)	Avg. # of Firms (in 1000's)	Fraction Total Emp. (%)	Avg. Emp. per Plant	Cyclical Prop. # Workers per Est.		
				Avg. # worker per Est. w/ gdp		Elas. w/ GDP
				below trend	above trend	
1 to 4	1908.71	6.55	2.31	2.3065	2.315	0.137
5 to 9	736.37	7.32	6.59	6.561	6.6208	0.385*
10 to 19	407.70	8.40	12.68	12.6129	12.759	0.346*
20 to 49	237.02	11.01	24.43	24.2209	24.651	0.302
50 to 99	71.04	7.54	40.23	39.6674	40.8219	0.452
100 to 249	35.00	8.20	51.44	50.5698	52.3573	0.897*
250 to 499	9.77	5.16	59.00	58.205	59.8447	0.706*
500 to 999	4.68	4.81	63.17	63.037	63.3069	0.312
1000 to 2499	3.04	6.52	66.13	65.4618	66.8366	0.479*
2500 to 4999	1.11	4.77	60.53	60.1928	60.8968	0.080
5000 +	1.45	29.74	75.81	75.7357	75.899	0.127

Note: The source is U.S. Census Bureau, Business Dynamics Statistics (BDS) Data Tables. We extract a linear trend component to all variables. The "Avg. # of Firms" corresponds to the average number of firms in each size bin over our sample (in thousands). "Fraction Total Emp." is computed as the average of total employees in each size bin divided by total employment. "Avg. Emp. per Plant" corresponds to the average of the number of employees per establishment in each size cathegory. "Avg. # Worker per Est. when GDP is below and above trend" is derived from a linear regression of average number of workers per establishment by firm size on a constant, a linear trend and a dummy that identifies periods where GDP is above trend. The value reported is the parameter on this dummy. GDP corresponds to log-real GDP. The trend for GDP is computed using the H-P filter with parameter 6.25. "Elas. w/ GDP" corresponds to the elasticity between the average number of workers per establishment by firm size and detrended GDP. This elasticity is derived from a linear regression of log average number of workers per establishment by firm size on a constant, a linear trend and log real detrended GDP. * denotes significant at the 10%.

Table 20: Averages with and without a time trend

Firm Size (# workers)	Avg. # of firms in 1000's		Fraction Total Emp.		Avg. Emp. Per plant	
	detrended	Non-detrended	detrended	Non-det.	detrended	Non-det.
1 to 4	1908.71	2437.26	6.55	5.78	2.31	2.23
5 to 9	736.37	941.08	7.32	6.63	6.59	6.54
10 to 19	407.70	541.73	8.40	7.82	12.68	12.75
20 to 49	237.02	328.85	11.01	10.62	24.43	24.62
50 to 99	71.04	102.05	7.54	7.47	40.23	40.07
100 to 249	35.00	53.62	8.20	8.54	51.44	49.89
250 to 499	9.77	15.39	5.16	5.46	59.00	54.07
500 to 999	4.68	7.25	4.81	5.01	63.17	58.40
1000 to 2499	3.04	4.64	6.52	6.81	66.13	62.86
2500 to 4999	1.11	1.76	4.77	5.15	60.53	58.93
5000 +	1.45	2.18	29.74	30.72	75.81	61.80

Note: The source is U.S. Census Bureau, Business Dynamics Statistics (BDS) Data Tables. The "Avg. # of Firms" corresponds to the average number of firms in each size bin over our sample (in thousands). "Fraction Total Emp." is computed as the average of total employees in each size bin divided by total employment. "Avg. Emp. per Plant" corresponds to the average of the number of employees per establishment in each size category.

A1.5 Market Exposure and Volatility: Robustness Checks

Table 21 presents the estimates from equation (25) using the number of SIC codes, as well as SGA expenses and Advertising expenses using the compustat-segment database. We incorporated size and age as additional controls (in addition to the firm fixed effects, the year-industry fixed effects and the time trend).

Table 22 presents the estimates from equation (25) using the number of establishments, MSAs and the product of SIC codes and establishments using the compustat-LBD database. In this table too, we incorporated size and age as additional controls (in addition to the firm fixed effects, the year-industry fixed effects and the time trend).

Observe that the relationship between our measures of market exposure (SIC codes, establishments, MSA, SIC*establishments, SGA expenses, and advertising expenses) and firm-level volatility is robust to the incorporation these additional controls. The coefficient on the appropriate market exposure measure is negative in all our specifications other than in the case of the number of SIC codes, and the product of SIC codes and establishments when size is used as a control. Moreover, the introduction of size as a control makes the estimates on market exposure non significant. Note that this is an expected result from our theoretical model given the high correlation between the number of markets a firm decides to participate in and the total number of employees the firm has. In the data, the measures of market exposure and employment are also highly correlated with correlation coefficients of up to 0.47.

Finally, table 23 reports the elasticity of the firm-level volatility to additional number of market exposure measures. We look at the number of SIC codes, number of establishments, number of MSA, as well as their interactions. All of these variations of the market exposure measure deliver very close elasticities between 9% and 13%.

Table 21: Market Exposure and Firm-Level Idiosyncratic Volatility I

	Dependent Variable $\ln(\epsilon^2_{ijt})$								
$\ln(numberSICs)$	-	-	-	-	-	-	-0.137	-0.043	0.013
Std Error	-	-	-	-	-	-	0.021***	0.021**	0.022
$\ln(expenses_{ijt})$	-0.299	-0.228	-0.096	-	-	-	-	-	-
Std Error	0.010***	0.01***	0.015***	-	-	-	-	-	-
$\ln(advertising_{ijt})$	-	-	-	-0.126	-0.095	-0.011	-	-	-
Std Error	-	-	-	0.012***	0.012***	0.014	-	-	-
$\ln(size_{ijt})$	-	-	-0.252	-	-	-0.304		-	-0.306
Std Error	-	-	0.014***	-	-	0.021***		-	0.010***
$\ln(age_{ijt})$	-	-0.451	-	-	-0.541	-		-0.559	-
Std Error	-	0.014***	-	-	0.026***	-		0.016***	-
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. Obs.	184548	184548	184548	70003	70003	70003	155175	155175	155175
R-squared	0.0455	0.0511	0.0473	0.0348	0.0417	0.0382	0.0178	0.0264	0.0243
Sample	Compustat								
Years	1960-2012								

Note: *** denotes significant at the 1% level, ** at the 5% level and * at the 10% level. $\ln(\epsilon^2_{ijt})$ is constructed from the estimated residual of equation (1). $\ln(expenses_{ijt})$ is constructed as log real selling, general and administrative expenses (SGA) and $\ln(advertising_{ijt})$ corresponds to Advertising Expenses (XAD). Industry deflators are used in every case. $\ln(size)$ corresponds to log-employment as in equation (1). The age of the firm corresponds to the number of years in the Compustat sample. $\ln(numberSICs)$ corresponds to four-digit SIC codes as reported in the Compustast Segment Data.

Table 22: Market Exposure and Firm-Level Idiosyncratic Volatility II

	Dependent Variable $\ln(\epsilon^2_{ijt})$								
$\ln(numberEstabl_{ijt})$	-	-	-	-	-	-	-0.0808	-0.0461	-0.0048
Std Error	-	-	-	-	-	-	0.00882***	0.00887***	0.00944
$\ln(numberMSA_{ijt})$	-0.0941	-0.0525	-0.00179	-	-	-	-	-	-
Std Error	0.010***	0.0103***	0.0109	-	-	-	-	-	-
$\ln(SIC * Est_{ijt})$	-	-	-	-0.075	-0.0368	0.00437	-	-	-
Std Error	-	-	-	0.00805***	0.00813***	0.00875	-	-	-
$\ln(size_{ijt})$	-	-	-0.282	-	-	-0.283		-	-0.283
Std Error	-	-	0.012***	-	-	0.012***		-	0.012***
$\ln(age_{ijt})$	-	-0.558	-	-	-0.558	-		-0.558	-
Std Error	-	0.019***	-	-	0.019***	-		0.019***	-
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. Obs.	129724	129724	129724	124433	124433	124433	129724	129724	129724
R-squared	0.018	0.0251	0.0227	0.0183	0.0253	0.0228	0.018	0.02561	0.0227
Sample	Compustat - LBD								
Years	1977-2011								

Note: *** denotes significant at the 1% level, ** at the 5% level and * at the 10% level. $\ln(\epsilon^2_{ijt})$ is constructed from the estimated residual of equation (1). Industry deflators are used in every case. $\ln(size)$ corresponds to log-employment as in equation (1). The age of the firm corresponds to the number of years in the Compustat LBD sample. $\ln(numberSICs)$ corresponds to four-digit SIC codes as reported in the Compustast LBD Data. The source for the number of establishments and MSA is the Compustat-LBD database.

Table 23: Market Exposure and Firm-Level Idiosyncratic Volatility III

	Dependent Variable $\ln(\epsilon^2_{ijt})$								
$\ln(numberSICs)$	-0.137	-	-	-	0.0065	-	0.017	-	-
Std Error	0.0212***	-	-	-	0.028	-	0.028	-	-
$\ln(numberestabs.)$	-	-0.081	-	-	(omitted)	-	-	-	(omitted)
Std Error	-	0.009***	-	-	-	-	-	-	-
$\ln(numberMSAs)$	-	-	-0.094	-	-	-	(omitted)	-	-0.012
Std Error	-	-	0.01***	-	-	-	-	-	0.057
$\ln(SICs * estabs.)$	-	-	-	-0.075	-0.076	-	-	-	-
Std Error	-	-	-	0.008***	0.009***	-	-	-	-
$\ln(SICs * MSAs)$	-	-	-	-	-	-0.085	-0.088	-	-
Std Error	-	-	-	-	-	0.009***	0.011***	-	-
$\ln(estabs. * MSAs)$	-	-	-	-	-	-	-	-0.045	-0.039
Std Error	-	-	-	-	-	-	-	0.005***	0.027
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. Obs.	155175	129724	129724	124433	124433	124433	124433	129724	129724
R-squared	0.0178	0.018	0.018	0.0183	0.0183	0.0183	0.0183	0.018	0.018
Sample	Compustat	LBD-Compustat Link							
Years	1960-2012	1977-2011							

Note: *** denotes significant at the 1% level, ** at the 5% level and * at the 10% level. $\ln(\epsilon^2_{ijt})$ is constructed from the estimated residual of equation (1). $\ln(numberSICs)$ corresponds to four-digit SIC codes as reported in the Compustast Segment Data. $\ln(numberestabs.)$ corresponds to the number of establishments each firm owns as derived from our sample that links Compustast with the LBD. $\ln(numberMSAs)$ corresponds to the number of MSA's where the establishments a firm owns are located also from the Compustat-LBD link. Some variables were automatically omitted due to collinearity.