Demand Uncertainty and Cost Behavior

Author(s): Rajiv D. Banker, Dmitri Byzalov and Jose M. Plehn-Dujowich

Source: *The Accounting Review*, MAY 2014, Vol. 89, No. 3 (MAY 2014), pp. 839-865

Published by: American Accounting Association

Stable URL: https://www.jstor.org/stable/24468320

Demand Uncertainty and Cost Behavior

Rajiv D. Banker
Dmitri Byzalov
Temple University

Jose M. Plehn-Dujowich
Saint Mary's College of California

ABSTRACT: We investigate analytically and empirically the relationship between demand uncertainty and cost behavior. We argue that with more uncertain demand, unusually high realizations of demand become more likely. Accordingly, firms will choose a higher capacity of fixed inputs when uncertainty increases in order to reduce congestion costs. Higher capacity levels imply a more rigid short-run cost structure with higher fixed and lower variable costs. We formalize this "counterintuitive" argument in a simple analytical model of capacity choice. Following this logic, we hypothesize that firms facing higher demand uncertainty have a more rigid short-run cost structure with higher fixed and lower variable costs. We test this hypothesis for the manufacturing sector using data from Compustat and the NBER-CES Industry Database. Evidence strongly supports our hypothesis for multiple cost categories in both datasets. The results are robust to alternative specifications.

Keywords: cost behavior; demand uncertainty; cost rigidity.

Data Availability: All data used in this study are available from public sources.

I. INTRODUCTION

Understanding cost behavior is one of the fundamental issues in cost accounting. In this paper, we focus on the role of demand uncertainty in cost behavior. Demand uncertainty is likely to affect managers' commitments of "fixed" activity resources,[1] which are chosen before actual demand is realized. From a manager's perspective, realized demand can be viewed as

---

[1] As we illustrate in Section II, "fixed" activity resources such as skilled indirect labor account for a far greater share of costs than depreciation on physical capital such as property, plant, and equipment. Therefore, we focus on managers' commitments of activity resources, which are distinct from, and conditional on, longer-term capital investment decisions.

839

a random variable drawn from a certain distribution, and demand uncertainty characterizes the variance of this distribution. In choosing committed capacity levels, managers have to consider the full range of likely demand realizations. Therefore, demand uncertainty is likely to affect their resource commitments, which, in turn, affect the mix of fixed and variable costs in the short-run cost structure of the firm.[2] We ask whether firms that face greater demand uncertainty tend to have a less rigid cost structure with lower fixed and higher variable costs, or a more rigid cost structure with higher fixed and lower variable costs. Our results are contrary to commonly held beliefs based on less formal analysis of the issue.

The traditional textbook intuition in accounting asserts that firms facing higher uncertainty associated with demand or various other circumstances should prefer a less rigid short-run cost structure with lower fixed and higher variable costs. For example, in their managerial accounting textbook, Balakrishnan, Sivaramakrishnan, and Sprinkle (2008, 171) explain that "a cost structure with less operating leverage [i.e., a lower proportion of fixed costs] offers companies *flexibility* because it involves fewer upfront cost commitments (i.e., fewer fixed costs). Companies confronting uncertain and fluctuating demand conditions are likely to opt for this flexibility" (emphasis in the original). Kallapur and Eldenburg (2005, 736), who focus on contribution margin uncertainty,[3] argue that "because the value of flexibility increases with uncertainty, technologies with high variable and low fixed costs become more attractive as uncertainty increases." Such conventional wisdom is also pervasive among the industry practitioners. For example, Boston Consulting Group offers the following advice: "Fixed costs can be transformed into variable costs through a process known as *variabilization*. Organizations that variabilize their costs can master the business cycle rather than be whipped by it" (emphasis in the original).[4] Thus, the traditional view in accounting suggests that firms facing higher uncertainty should opt for arrangements that result in a less rigid short-run cost structure with lower fixed and higher variable costs.

Although this traditional intuition is pervasive among accounting researchers and practitioners, we argue that it is often not interpreted accurately in the context of *demand* uncertainty, i.e., variability of realized demand. On the contrary, in Section II we identify conditions under which, when managers face higher demand uncertainty, their optimal longer-term capacity commitments will lead to a *more* rigid short-run cost structure with *higher* fixed and *lower* variable costs. The reason is that higher demand uncertainty increases the likelihood of both unusually low and unusually high demand realizations. Unusually high demand realizations are associated with disproportionately large costs of congestion due to limited capacity of the fixed inputs. Thus, when demand uncertainty increases, congestion becomes both more frequent and more severe. Therefore, managers increase the capacity of the fixed inputs to relieve the congestion. In turn, the increase in the fixed inputs implies higher fixed and lower variable costs, i.e., a more rigid short-run cost structure.

---

[2] Fixed and variable costs are short-run concepts, and "in the long run all costs are variable" in the sense that all resources are subject to managerial discretion in the long run (e.g., Noreen and Soderstrom 1994). Costs are caused by resources, including both activity resources and physical capital; cost behavior reflects resource adjustment in response to activity changes. Some resources, such as skilled indirect labor, are costly to adjust in the short run, and therefore are committed in advance, causing fixed costs. Other resources, such as direct materials, can be adjusted flexibly in the short run, and therefore are consumed as needed based on realized demand, giving rise to variable costs. Thus, whether a cost is fixed or variable depends on the level of adjustment costs for the underlying resource (Banker and Byzalov 2013), which varies with the time horizon, contractual and institutional arrangements, and technological constraints.

[3] A firm may face uncertainty about many factors that affect its financial performance. Accounting textbooks frequently focus on demand uncertainty in the context of cost-volume-profit analysis. Our results should therefore be interpreted cautiously in light of the particular, but conventional, context of the demand uncertainty that we consider.

[4] Source: http://www.bcg.com/documents/file15466.pdf

This argument leads us to hypothesize that firms facing higher demand uncertainty should have a more rigid short-run cost structure with higher fixed and lower variable costs. We test this hypothesis empirically for the manufacturing sector, relying on variation in uncertainty across firms and industries. We use firm-level data from Compustat between 1979–2008, and industry-level data from the NBER-CES Manufacturing Industry Database between 1958–2005. The NBER-CES dataset, described in detail in Section III, is based on an annual sample of approximately 60,000 manufacturing establishments and is representative of the entire universe of both public and private manufacturing firms in the U.S. It contains detailed annual data for each of the 473 six-digit NAICS manufacturing industries, including data on sales and total employees, corresponding to firm-level sales and employment variables in Compustat, as well as more detailed data on inputs that do not have an analogue in Compustat, including production workers, payroll, production hours, non-production employees, cost of materials, and cost of energy.

To characterize firms' short-run cost structure, we regress annual log-changes in costs on contemporaneous annual log-changes in sales revenue.[5] The slope coefficient in this regression approximates the percentage change in costs for a 1 percent change in sales. A greater slope indicates a short-run cost structure with a lower proportion of fixed costs and a higher proportion of variable costs (Kallapur and Eldenburg 2005), which we term a less rigid cost structure. For brevity, we will use the term "cost rigidity" to denote the mix of fixed and variable costs in the short-run cost structure of a firm, and will interpret the regression slope as our empirical measure of cost rigidity.

To capture the relationship between demand uncertainty and cost rigidity in estimation, we introduce an interaction term between the log-change in sales and demand uncertainty, such that the slope on log-change in sales becomes a function of demand uncertainty. If greater demand uncertainty increases the slope such that costs change to a greater extent for the same change in sales, then higher demand uncertainty is associated with a less rigid short-run cost structure with lower fixed and higher variable costs. Conversely, if greater demand uncertainty reduces the slope, then higher demand uncertainty is associated with a more rigid short-run cost structure with higher fixed and lower variable costs. We measure demand uncertainty for firm i (industry i) as the standard deviation of log-changes in sales for that firm (industry). In robustness checks, we use several additional measures of demand uncertainty, yielding similar results.

In agreement with our hypothesis, our results indicate that greater demand uncertainty is associated with a lower slope on contemporaneous log-changes in sales, i.e., a more rigid short-run cost structure with higher fixed and lower variable costs. This pattern is statistically and economically significant for multiple cost categories, including physical quantities of key labor inputs, both in the firm-level sample from Compustat and in the industry-level sample from the NBER-CES Industry Database. The cost categories include SG&A costs, COGS, and number of employees in the Compustat sample; and the number of employees, payroll, production workers, production hours, non-production workers, and costs of energy in the NBER-CES sample.[6] The results continue to hold in robustness checks that include alternative measures of demand

---

[5] Since we cannot directly observe the mix of fixed and variable costs in the cost structure, we infer it from the short-run cost response to sales changes. Similar specifications are common in the literature, e.g., Noreen and Soderstrom (1994, 1997), Anderson, Banker, and Janakiraman (2003), Kallapur and Eldenburg (2005). We estimate the cost structure, and not the underlying capacity decisions, for two reasons. First, the mix of fixed and variable costs is a widely used metric of cost behavior in accounting. Second, for activity resources that play a central role in cost behavior, such as skilled indirect labor, we do not observe the underlying capacity commitments, and therefore we have to infer them from the cost structure.

[6] We do not expect to find any significant effect of uncertainty for the cost of materials because managers can deal with uncertainty for materials by using inventories. As expected, the relationship between demand uncertainty and cost rigidity for materials is insignificant.

uncertainty, additional estimation methods that allow for long-term structural changes and other types of heterogeneity both in the cross-section and over time, and with controls for numerous short-term and long-term factors that may affect cost behavior.

While the empirical results support our prediction that increased demand uncertainty leads to a more rigid cost structure, the conventional wisdom of adopting a more variable cost structure may be warranted as a response to a related, but qualitatively different, phenomenon—an increase in *downside risk*.[7] Higher downside risk means that only unfavorable demand realizations become more likely, which not only increases the variance of demand, but also reduces the *mean* of demand. By contrast, demand uncertainty affects the variance but not the mean, as illustrated in Figure 1. Because congestion costs are lower at more unfavorable demand realizations, an increase in downside risk reduces expected costs of congestion. Given reduced congestion, managers choose a lower capacity level, leading to a less rigid short-run cost structure in the case of increased downside risk. By contrast, in the case of increased demand uncertainty, expected congestion costs are higher, resulting in higher capacity commitments and a more rigid cost structure. Thus, the conventional wisdom may be justified in the context of increased *downside risk*, but as we show both theoretically and empirically, not in the context of increased demand *uncertainty*.[8]

Section II next develops our hypothesis about the relationship between demand uncertainty and cost rigidity, and relates it to the relevant literature. Section III describes the two samples and our empirical research design. Section IV presents the empirical results. Section V concludes and relates the traditional intuition to our analysis.

II. HYPOTHESIS DEVELOPMENT

Understanding cost behavior is one of the fundamental issues in cost accounting, and numerous prior studies have explored various aspects of it. Miller and Vollman (1985), Cooper and Kaplan (1987), Foster and Gupta (1990), Banker and Johnston (1993), Datar, Kekre, Mukhopadhyay, and Srinivasan (1993), Banker, Potter, and Schroeder (1995), and others analyze non-volume-based cost drivers. Noreen and Soderstrom (1994, 1997) test the proportionality hypothesis for overhead costs. Anderson et al. (2003), Weiss (2010), Chen, Lu, and Sougiannis (2012), Dierynck, Landsman, and Renders (2012), Banker, Byzalov, Ciftci, and Mashruwala (2014), Kama and Weiss (2013), and others explore sticky cost behavior. Kallapur and Eldenburg (2005), which we discuss later, is one of the few studies that analyze the role of uncertainty in cost behavior; however, they focus on a different type of uncertainty that was caused by a change in Medicare reimbursement policy.

We characterize cost behavior in terms of *cost rigidity*, the mix of fixed and variable costs in the short-run cost structure of the firm, operationalized in terms of the slope in a regression of log-changes in costs on contemporaneous log-changes in sales. The regression slope β approximates the percentage change in costs for a 1 percent change in sales:

$$\beta = \frac{\partial \ln C(q)}{\partial \ln q} = \frac{\partial C(q)/C(q)}{\partial q/q}, \tag{1}$$

---

[7] For example, Mao (1970) and March and Shapira (1987) find in broad-based surveys that executives tend to view uncertainty (risk) in terms of unfavorable outcomes rather than in terms of variance of outcomes.

[8] Holding capacity constant, an increase in downside risk will also result, on average, in increased idle capacity, decreased margin of safety, and increased operating leverage, all of which will indicate the need to reduce capacity in response to the downward shift in demand. By contrast, because demand uncertainty does not affect the expected level of demand, it will have no direct effect on these standard metrics of operating risk. Thus, the standard textbook measures of operating risk are designed to reflect downside risk rather than uncertainty.
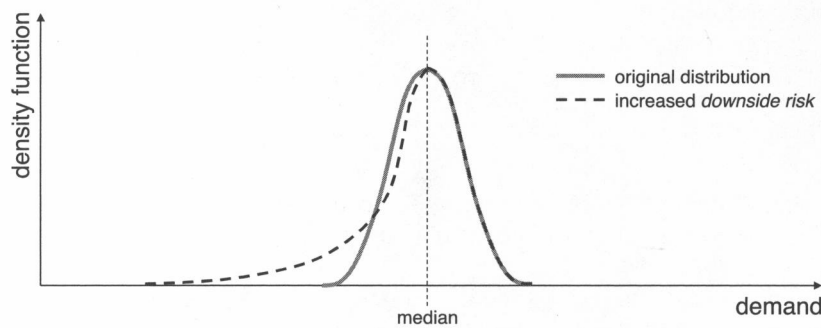
FIGURE 1
Increased Demand Uncertainty versus Increased Downside Risk

Panel A: Increased Demand Uncertainty
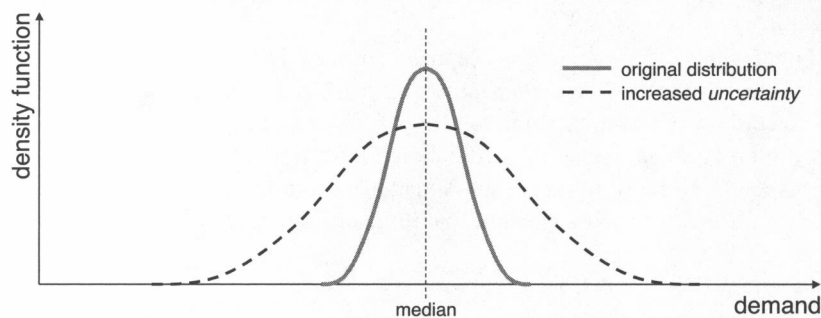
The figure depicts the original demand distribution (the solid line) and the new demand distribution after an increase in demand uncertainty (the dashed line).

Panel B: Increased Downside Risk

The figure depicts the original demand distribution (the solid line) and the new demand distribution after an increase in downside risk (the dashed line).

where $C(q)$ represents the short-run cost function and q represents sales volume.[9]

The slope β in (1) can also be interpreted as the ratio of marginal cost $\partial C(q)/q$ to average cost $C(q)/q$ (Noreen and Soderstrom 1994). Further, if total costs are linear in volume, i.e., the marginal cost is equal to a constant unit variable cost v, then the slope β has an additional interpretation as the ratio of variable costs vq to total costs $C(q)$ (Kallapur and Eldenburg 2005). In both cases, a greater slope β corresponds to a less rigid short-run cost structure, in which costs change to a greater extent for the same contemporaneous change in sales.

[9] In the empirical analysis, we use deflated sales revenue as a proxy for volume. This approach is standard in the literature, e.g., Anderson et al. (2003), Kallapur and Eldenburg (2005).

A large literature focuses on the related notion of cost stickiness. Cost stickiness refers to the degree of asymmetry in the response of costs to contemporaneous sales increases and decreases, and reflects the consequences of managers' short-term resource adjustment decisions that are made *ex post*, after observing actual demand (Anderson et al. 2003). In contrast, cost rigidity characterizes the average magnitude of the response of costs to contemporaneous sales changes, and reflects the consequences of managers' longer-term capacity choices that are made *ex ante*, prior to observing realized demand.

Demand uncertainty affects managers' capacity choices. The traditional intuition in accounting suggests that when managers face higher uncertainty, including higher *demand* uncertainty, they prefer a less rigid short-run cost structure with lower fixed and higher variable costs, leading to a negative association between demand uncertainty and cost rigidity. However, we argue below that if managers respond optimally to increased demand uncertainty, then their capacity choices will lead to a *more rigid* short-run cost structure with *higher* fixed and *lower* variable costs.

Optimal Capacity Choice and Cost Structure

We consider the optimal choice of resource commitments for a risk-neutral firm facing uncertain demand in a simple model. The firm uses an exogenously given production technology with two inputs, a "fixed" input x that is chosen before actual demand is known, and a "variable" input z that is chosen after observing realized demand. In the short run, input x is constant, causing fixed costs, whereas input z varies with production volume q, creating variable costs. Managers' choice of the level of the fixed input x determines the mix of fixed and variable costs in the short-run cost structure of the firm.

The production technology of the firm is described by the production function $f(x,z)$. We specify $f(x,z)$ as a translog production function (Christensen, Jorgenson, and Lau 1973):

$$\ln f(x, z) = \alpha_0 + \alpha_1 \ln x + \alpha_2 \ln z + \frac{\beta_{11}}{2}(\ln x)^2 + \beta_{12}\ln x \ln z + \frac{\beta_{22}}{2}(\ln z)^2. \tag{2}$$

The translog specification provides a flexible local second-order Taylor series approximation for a general production function. It includes the Cobb-Douglas production function when $\beta_{11} = \beta_{12} = \beta_{22} = 0$.

In the short run, the consumption of the variable input z is determined by the production volume q. We denote by $z^*(q|x)$ the quantity of input z required to generate volume q for a given level of the fixed input x, so that:

$$z^*(q \mid x) = z : f(x, z) = q. \tag{3}$$

Conditional on the fixed input x, the short-run cost function $C(q|x)$ is:

$$C(q \mid x) = p_x x + p_z z^*(q \mid x), \tag{4}$$

where p_x, p_z are the input prices, $p_x x$ represents the fixed costs, and $p_z z^*(q|x)$ represents the variable costs.[10] When managers increase the fixed input x, the fixed costs $p_x x$ are increased, whereas the variable costs $p_z z^*(q|x)$ and the marginal costs $p_z \frac{\partial z^*(q|x)}{\partial q}$ are reduced because the increase in the fixed input x relieves the congestion for the variable input z (Lemma 1). Therefore, a higher x corresponds to a more rigid short-run cost structure with higher fixed and lower variable costs.

---

[10] $p_z z^*(q|x)$ is a variable cost in the sense that it varies with volume; however, it is not strictly proportional to volume. Accounting research and practice typically use a linear approximation of the cost function. However, this linear approximation cannot capture the effect of demand uncertainty on expected costs; therefore, we derive the cost function from microeconomic foundations.

The short-run cost function $C(q|x)$ is convex in volume q, i.e., the marginal cost $p_z \frac{\partial z^*(q|x)}{\partial q}$ is upward-sloping in q (Lemma 2). When volume q goes up, the congestion for the variable input z gets worse because the fixed input x stays constant while input z increases. Increased congestion reduces the marginal productivity of input z and increases the marginal costs. Consequently, the cost function $C(q|x)$ is convex in volume. Due to convexity, an increase in demand uncertainty increases expected total costs $E(C(q|x))$. In other words, demand uncertainty is costly for the firm because congestion costs are disproportionately large at high demand realizations, which become more likely when uncertainty goes up.[11]

To construct a simple model that focuses on costs, we treat the distribution of quantity demanded q^d as exogenously given, and assume that it is always optimal for the firm to fully meet the demand. We also assume away inventories.[12] Thus, production volume q is always equal to the quantity demanded q^d. We assume that the demand follows:

$$q^d = q_0 + \sigma\varepsilon, \tag{5}$$

where q_0 represents the mean level of demand, $\varepsilon \sim G(...)$ is a random demand shock with zero mean and unit variance that follows the cumulative distribution function $G(...)$, and σ is a positive parameter that determines the magnitude of demand uncertainty. An increase in demand uncertainty σ increases the variation of demand around its mean q_0, without affecting the mean level of demand or the shape of its distribution.

Because the fixed input x is chosen prior to observing actual demand q^d, the optimal choice of x aims to minimize expected total costs given the distribution of demand:

$$\min_x \left\{ p_x x + E\left(p_z z^*(q_0 + \sigma\varepsilon | x) \right) \right\}, \tag{6}$$

where the expectation is over the realizations of the demand shock ε and production volume is equal to the quantity demanded, i.e., $q = q_0 + \sigma\varepsilon$.

The first-order condition becomes:

$$p_x = -p_z E\left[\frac{\partial z^*(q_0 + \sigma\varepsilon | x)}{\partial x} \right]. \tag{7}$$

The left-hand side in this condition represents the incremental fixed cost of adding an extra unit of input x. The right-hand side represents the corresponding expected benefits, or savings in variable costs of input z. Specifically, an increase in the fixed input x relieves the congestion, which makes the variable input z more productive and, therefore, reduces the amount of z required to generate the same output. At the optimum, the expected benefits from an extra unit of input x are exactly offset by its incremental fixed cost.

Next, we examine how an increase in demand uncertainty σ affects the optimal choice of the fixed input x. In turn, this will determine the relationship between demand uncertainty and cost rigidity, since higher x corresponds to a more rigid short-run cost structure with higher fixed and lower variable costs.

---

[11] Low demand realizations, associated with low congestion costs, also become more likely. However, due to convexity, the disproportionately large congestion costs at high demand realizations dominate. This intuition is similar to that in Banker, Datar, and Kekre (1988).

[12] Inventories would allow the firm to smooth out production volume when sales fluctuate. However, as long as such production smoothing is not perfect, greater sales variability will lead to greater production volume variability, in which case our analysis continues to be relevant.

The Relationship between Demand Uncertainty and Cost Structure

Higher demand uncertainty σ increases the likelihood of both unusually high and unusually low realizations of demand, which affects the expected benefits on the right-hand side of (7). For higher levels of demand, congestion is severe, and an increase in the fixed input x reduces the variable costs significantly by relieving this congestion. For lower levels of demand, congestion is less serious, and an increase in the fixed input x reduces the variable costs less significantly given less initial congestion. Thus, the cost savings from an extra unit of the fixed input x are large at high demand realizations but small at low demand realizations, both of which become more likely when demand uncertainty goes up.

As we prove in Appendix A, under mild regularity conditions on the production function, the large cost savings at high demand realizations outweigh the small cost savings at low demand realizations. Therefore, when demand uncertainty is higher, the expected value of cost savings in (7) increases, leading to a higher optimal choice of the fixed input x.

The intuition for this prediction is that when demand uncertainty goes up, expected costs of congestion become more important. An increase in the fixed input x relieves the congestion. Further, the expected reduction in congestion is larger when demand uncertainty is higher, leading to a higher optimal choice of input x. In other words, when demand uncertainty goes up, it is optimal to increase the capacity of the fixed input x to relieve the congestion that is becoming more frequent and more severe.

For the translog production function (2), this argument holds whenever the following sufficient conditions on output elasticities, percentage changes in output for a 1 percent change in an input, hold in the relevant range. First, both output elasticities should be above 0 and less than 1, meaning that output increases less than proportionately when one of the inputs is increased and the other is held constant. This condition holds in the case of constant, decreasing, and mildly increasing returns to scale. Second, output elasticity for each input should be non-increasing with respect to that input. This condition ensures that when only one of the two inputs is increased, marginal productivity of that input is diminished, reflecting an increase in congestion. Third, output elasticity for each input should be non-decreasing with respect to the other input. This condition implies that an increase in one of the inputs raises the marginal productivity of the other input, representing a reduction in congestion for the latter.[13]

We summarize these conditions in Proposition 1.

Proposition 1: Demand Uncertainty and the Optimal Choice of the Fixed Input: If the production function has the following properties for both inputs x and z everywhere in the relevant range:

(1) when only one of the inputs is increased, output increases less than proportionately;
(2) when only one of the inputs is increased, output elasticity for that input decreases or remains constant, reflecting increased congestion; and
(3) when the other input is increased, output elasticity for a given input increases or remains constant, reflecting reduced congestion;

then the optimal level of the fixed input x is increasing in demand uncertainty σ.

---

[13] The second and third conditions imply increased and reduced congestion, respectively, even if the corresponding output elasticity remains constant. For example, the marginal product of input x can be rewritten as $f_x = (\partial \ln f / \partial \ln x)(f/x)$. Even if the output elasticity $\partial \ln f / \partial \ln x$ remains constant, the marginal product f_x in the second condition is strictly decreasing in x, representing higher congestion, because output f expands less than proportionately with changes in x. Similarly, the marginal product f_x in the third condition is strictly increasing in input z, corresponding to less congestion, because output f is increasing in z.

Proof: See Appendix A.

Proposition 1 implies that higher demand uncertainty should be associated with greater cost rigidity in the form of higher fixed and lower variable costs in the short-run cost function. Greater cost rigidity corresponds to a lower slope in regression of log-changes in costs on log-changes in sales, leading to the following hypothesis:

> **H1:** The slope in a regression of log-change in costs on contemporaneous log-change in sales, our empirical measure of cost rigidity, is decreasing in demand uncertainty.

Kallapur and Eldenburg (2005) have examined the relationship between uncertainty and the mix of fixed and variable costs in the specific context of Medicare reimbursement for hospitals. Appealing to the real options theory of investment (McDonald and Siegel 1985, 1986; Dixit and Pindyck 1994; Mauer and Ott 1995; Arya and Glover 2001), Kallapur and Eldenburg (2005) argue that higher uncertainty should lead firms to choose technologies with lower fixed and higher variable costs. While their theoretical argument is couched in terms of general uncertainty, their findings should be interpreted cautiously because they are based on a specific empirical scenario involving a transition from cost-based reimbursement to a flat-fee prospective payment system. Thus, unique institutional details of Medicare reimbursement influence Kallapur and Eldenburg's (2005) findings, and these findings do not necessarily generalize to other institutional arrangements and other types of uncertainty, including demand uncertainty.[14]

Prior literature in economics has examined the effects of uncertainty in the context of capital investment. Studies by Hartman (1972), Abel (1983), Caballero (1991) and Abel and Eberly (1994) show that under perfect competition and constant returns to scale, greater *price* uncertainty increases the optimal investment and capital stock. Although similar to our predictions for demand uncertainty, an important distinction is that although price uncertainty increases capital investment and capital stock in these papers, it does *not* affect the short-run mix of fixed and variable costs—in contrast to our predictions.[15]

A second stream of studies, including Pindyck (1988) and some of the models in Caballero (1991) and Abel and Eberly (1994), shows that irreversible capital investment combined with a diminishing marginal revenue product of capital may generate a negative relationship between demand uncertainty and capital investment. These models rely crucially on partial or full irreversibility of capital investment, because irreversibility implies that managers are more concerned about having "too much" physical capital than about having "too little" (Caballero 1991). While irreversibility is likely to be important for physical capital such as plant and machinery, it is much less important for the activity resources that we focus on in the empirical

---

[14] Medicare reimbursement change had no direct effect on demand uncertainty, i.e., physical volume variability relevant for congestion costs; *contribution margin* uncertainty increased only because the new system changed the relationship between hospitals' reimbursement revenue and costs. Under the cost-based scheme, revenue and contribution margin were proportional to costs. Therefore, a more rigid cost structure would *reduce* contribution margin uncertainty due to lower cost variability. In the prospective payment system, by contrast, it would increase contribution margin uncertainty. The new reimbursement scheme also gave managers stronger incentives to contain capacity costs. Additionally, even in the context of increased demand uncertainty, managers' incentives to increase capacity are weaker in non-profits such as hospitals than in for-profit firms. Because non-profits likely place less emphasis on increasing profits for favorable demand realizations, managers are less willing to expand capacity to mitigate large congestion costs that arise only at high demand levels.

[15] These models focus on the optimal choice of fixed capital and variable labor. Due to constant returns to scale, the marginal product of labor depends only on the ratio of labor to capital, $MPL = h(L/K)$. Given the capital stock K and given the price of output p and the wage w, the optimal level of the variable labor input satisfies $ph(L/K) = w$. Therefore, the optimal ratio of labor to capital L/K is a function only of the prices p and w, and it does not depend on uncertainty or capital stock. In other words, greater uncertainty in these models increases both capital and labor proportionately, without changing the short-run mix of fixed and variable costs.

analysis, such as skilled indirect labor. Such activity resources account for a far greater share of operating costs than physical capital,[16] and, while fixed in the short run, they can be changed with minimal adjustment costs over a sufficiently long time horizon.[17] Thus, irreversibility is likely to be a second-order factor in the context of activity resources central to cost behavior.

III. RESEARCH DESIGN AND SAMPLE SELECTION

Estimation Model

We assume that the log-change in costs for firm i (industry i) follows:

$$\Delta \ln COST_{i,t} = \beta_0 + \beta_{i,t} \Delta \ln SALES_{i,t} + \gamma_0 controls_{i,t} + \varepsilon_{i,t}, \tag{8}$$

where $\Delta \ln COST_{i,t}$ represents the log-change in deflated costs for firm i from year $t-1$ to year t; $\Delta \ln SALES_{i,t}$ represents the log-change in deflated sales revenue for firm i from year $t-1$ to t; $controls_{i,t}$ are control variables; and $\varepsilon_{i,t}$ is a random shock. The slope $\beta_{i,t}$, which is specified in detail later, measures the percentage change in costs for a 1 percent change in sales revenue, and characterizes the degree of cost rigidity.[18]

Our use of a log-linear specification follows previous studies (e.g., Noreen and Soderstrom 1994, 1997; Banker et al. 1995; Anderson et al. 2003; Kallapur and Eldenburg 2005). Anderson et al. (2003) point out that the log-linear model has several advantages over a linear model. First, the log transformation makes variables more comparable across firms and industries, and alleviates heteroscedasticity. Second, like Anderson et al. (2003), we find that the Davidson and MacKinnon (1981) test rejects the linear model in favor of the log-linear model. Further, the coefficients in the log-linear model have a clear economic interpretation as percentage change in the dependent variable for a 1 percent change in the explanatory variable. The use of deflated sales revenue as a measure of volume follows prior studies (e.g., Anderson et al. 2003; Kallapur and Eldenburg 2005; Weiss 2010).[19]

---

[16] For example, in our Compustat sample, depreciation on physical capital accounts for just 4.6 percent of total operating costs on average, while resources captured in SG&A costs account for 27.1 percent, and resources captured in COGS account for 68.3 percent, where SG&A costs and COGS exclude estimated depreciation expense per Compustat data definitions.

[17] For example, Cooper and Kaplan (1992, 8) clarify why many activity resources are fixed in the short run: "Once decisions get made on resource availability levels in the organization, typically in the annual budgeting and authorization process, the expenses of supplying most resources will be determined for the year . . . For example, the resources committed to the purchase-order processing activity will be determined annually as a function of the expected number and complexity of purchase orders to be processed. We would not expect, however, the size of the purchasing department to fluctuate weekly or monthly depending on how many purchase orders get processed during a week or a month."

[18] The regression in changes captures primarily the short-run response of costs to concurrent changes in sales, i.e., it characterizes the short-run cost function. By contrast, a regression in levels would be dominated by cross-sectional differences across firms of different size and, therefore, would reflect the long-run expansion path of costs (Noreen and Soderstrom 1994).

[19] A few studies that focus on a single narrowly defined industry use physical volume measures (e.g., Noreen and Soderstrom 1994). However, even when data on physical outputs are available, this approach cannot be used in broad-based datasets spanning multiple industries. Because physical output units are not directly comparable across products, firms, and industries, physical volume has to be converted into a scale that is common across products, firms, and industries, using appropriate weights to aggregate different outputs. Sales revenue, which weighs different physical outputs in proportion to their relative prices, provides such a common scale. Undeflated sales revenue may be affected by price changes. By using *deflated* sales revenue, we control for changes in the aggregate price level; further, when we use the industry-specific deflators in the NBER-CES data, we also directly control for changes in relative prices both across and within industries.

We specify $\beta_{i,t}$, the slope on log-change in sales for firm i, as:

$$\beta_{i,t} = \beta_1 + \beta_2 UNCERT_i + \gamma_1 controls_{i,t}, \qquad (9)$$

where $UNCERT_i$ represents our empirical measure of demand uncertainty for firm i, and $controls_{i,t}$ are control variables. The coefficient β_2 captures the relationship between demand uncertainty and cost rigidity. If β_2 is positive, then higher uncertainty $UNCERT_i$ increases the slope $\beta_{i,t}$, corresponding to a less rigid short-run cost structure with lower fixed and higher variable costs. Conversely, if β_2 is negative, then higher uncertainty reduces the slope $\beta_{i,t}$, indicating a more rigid short-run cost structure. H1 implies that β_2 should be negative, i.e., higher demand uncertainty should be associated with greater cost rigidity.

We measure demand uncertainty $UNCERT_i$ for firm i as the standard deviation of log-changes in sales $\Delta \ln SALES_{i,t}$ for all valid observations of firm i. Because this standard deviation is computed separately for each firm, it captures variation in sales over time for each firm, but not variation across firms. The use of standard deviation as an empirical proxy for uncertainty is standard in the literature (e.g., Dechow and Dichev 2002; Kothari, Laguerre, and Leone 2002; Zhang 2006; Dichev and Tang 2009), and the standard deviation of log-changes in sales is commonly used as a measure of demand uncertainty in economics (e.g., Stock and Watson 2002; Comin and Philippon 2005; Comin and Mulani 2006; Davis and Kahn 2008). In robustness checks, we use two alternative measures of demand uncertainty, yielding similar results.

We use the following control variables. Because cost behavior likely varies across industries for technological reasons, we include three-digit NAICS industry dummies, both as stand-alone control variables in Equation (8), i.e., industry-specific intercepts, and as control variables in the slope Equation (9), i.e., industry-specific slopes. We also include GDP growth to control for aggregate trends in the economy. In robustness checks, we include additional control variables.

Combining Equations (8) and (9), we obtain our main estimation model:

Model A:
$$\begin{aligned} \Delta \ln COST_{i,t} &= \beta_0 + \beta_{i,t} \Delta \ln SALES_{i,t} + \gamma_0 controls_{i,t} + \varepsilon_{i,t}, \\ \beta_{i,t} &= \beta_1 + \beta_2 UNCERT_i + \gamma_1 controls_{i,t}, \end{aligned} \qquad (10)$$

where all variables were defined previously.

Our empirical measure of demand uncertainty, $UNCERT_i$, is computed based on a relatively small number of observations per firm. This leads to measurement error, which systematically biases the estimate of β_2 toward zero due to attenuation bias (Wooldridge 2002). Therefore, our estimates of β_2 yield a reliable *lower bound*, in absolute value, on the actual magnitude of the relationship between demand uncertainty and cost rigidity. Notably, the attenuation bias does not distort the sign of this relationship, and it does not lead to spurious findings of a significant relationship if in fact there is none. Further, although measurement error often distorts hypothesis tests, the standard t-test continues to be a valid test for the null hypothesis $\beta_2 = 0$.[20]

Sample Data

We use two estimation samples, a firm-level Compustat sample and an industry-level sample based on the NBER-CES Manufacturing Industry Database.

---

[20] Under the null $\beta_2 = 0$, the measurement error in $UNCERT_i$ is independent of the regression residual $\varepsilon_{i,t}$. Therefore, the attenuation bias does not apply, and OLS estimates and hypothesis tests have the standard properties despite the measurement error. In general in hypothesis testing, the distribution of the test statistic is determined under the assumption that the null hypothesis is true (e.g., DeGroot and Schervish 2002). Therefore, the attenuation bias that arises only when true $\beta_2 \neq 0$ does not affect the validity of hypothesis tests for the null $\beta_2 = 0$.

Compustat

We use data for all manufacturing firms (NAICS 31–33) from the Annual Fundamentals file between years 1979–2008. We focus on three cost categories: SG&A costs (Compustat mnemonic XSGA), COGS (mnemonic COGS), and number of employees (mnemonic EMP). We deflate all financial variables to control for inflation. The variable definitions are presented in Panel A of Table 1.

We discard firm-year observations if current or lagged sales or costs are missing, equal to zero, or negative. Following Anderson et al. (2003), in regressions for SG&A costs we discard observations if SG&A costs exceed sales in the current or prior year. In regressions for COGS, we drop observations if COGS exceeds sales by more than 50 percent in the current or prior year.[21] We also require firms to have at least ten valid observations for the computation of our empirical measure of demand uncertainty, $UNCERT_i$. To ensure that our estimates are not driven by outliers, we discard 1 percent of extreme observations on each tail for the regression variables. The final sample comprises 45,990 firm-year observations for SG&A costs, 51,016 observations for COGS, and 48,823 observations for the number of employees.

We present the descriptive statistics in Panel A of Table 2. The mean deflated sales revenue is $894.8 million, measured in average 1982–1984 dollars, and the median is $49.5 million. On average, SG&A costs and COGS account for 28.3 percent and 62.6 percent of sales revenue, respectively; the median is 24.4 percent and 65.3 percent, respectively. The average number of employees per firm is 5,790 and the median is 540.

Firms in the data face substantial demand uncertainty $UNCERT_i$, computed as the standard deviation of log-changes in sales $\Delta \ln SALES_{i,t}$ for all valid observations of firm i. The average $UNCERT_i$ is 0.35, and the median is 0.23.

NBER-CES Manufacturing Industry Database

Our second sample is based on the NBER-CES Manufacturing Industry Database. This database provides detailed industry-level data for each of the 473 six-digit NAICS manufacturing industries between 1958–2005.[22] The NBER-CES dataset has several notable features. First, it contains detailed data on inputs, including physical quantities for the labor inputs. Second, the industry definitions in the data are consistent over the entire sample period, which allows us to fully take advantage of the long panel dimension of the data. Third, because the NBER-CES database is derived from confidential *establishment*-level data, the industry-level variables are accurate even when they are based on firms operating in multiple industries. Further, the NBER-CES data reflect the full universe of both private and public manufacturing firms in the U.S. The data-collection process is described in Bartelsman and Gray (1996).

Most of the variables in the data come from the Annual Survey of Manufactures (ASM), which samples approximately 60,000 manufacturing establishments drawn from the Census of Manufactures. The ASM provides 11 variables in the NBER-CES data: number of employees, payroll, production workers, production hours, production worker wages, value of shipments, value added, end-of-year inventories, capital investment, expenditure on energy, and expenditure on materials.

We use the following variables from the NBER-CES data: sales revenue (*SALES*), number of employees (*EMP*), payroll (*PAYROLL*), number of production workers (*PRODE*), number of

---

[21] In downturns, COGS can exceed sales for firms that have a large proportion of fixed costs. The estimates are similar when we discard all observations for which COGS exceeds sales.

[22] The data are publicly available at http://www.nber.org/data/nbprod2005.html

TABLE 1

Variable Definitions

Panel A: Variable Definitions for the Firm-Level Compustat Sample

Explanatory Variables

$\Delta\ln SALES_{i,t}$	log-change in deflated sales (mnemonic SALE) of firm i from year $t-1$ to year t;
$UNCERT_i$	empirical proxy for demand uncertainty, computed as the standard deviation of $\Delta\ln SALES_{i,t}$ for all valid observations of firm i;
$GDPGROWTH_t$	GDP growth in year t; and
$IND1_i,\ldots,IND21_i$	three-digit NAICS industry dummies.

Dependent Variables

$\Delta\ln SGA_{i,t}$	log-change in deflated SG&A costs (mnemonic XSGA) of firm i from year $t-1$ to year t;
$\Delta\ln COGS_{i,t}$	log-change in deflated COGS (mnemonic COGS) of firm i from year $t-1$ to year t; and
$\Delta\ln EMP_{i,t}$	log-change in the number of employees (mnemonic EMP) of firm i from year $t-1$ to year t.

Panel B: Variable Definitions for the Industry-Level NBER-CES Sample

Explanatory Variables

$\Delta\ln SALES_{i,t}$	log-change in deflated sales (value of shipments) of six-digit NAICS industry i from year $t-1$ to year t, deflated using the industry-specific deflator for the value of shipments;
$UNCERT_i$	empirical proxy for demand uncertainty, computed as the standard deviation of $\Delta\ln SALES_{i,t}$ for all valid observations of industry i;
$GDPGROWTH_t$	GDP growth in year t; and
$IND1_i,\ldots,IND21_i$	three-digit NAICS industry dummies.

Dependent Variables

$\Delta\ln EMP_{i,t}$	log-change in the total number of employees of industry i from year $t-1$ to year t;
$\Delta\ln PAYROLL_{i,t}$	log-change in deflated total payroll of industry i from year $t-1$ to year t;
$\Delta\ln PRODE_{i,t}$	log-change in the number of production workers of industry i from year $t-1$ to year t;
$\Delta\ln PRODH_{i,t}$	log-change in the number of production worker hours of industry i from year $t-1$ to year t;
$\Delta\ln NPRODE_{i,t}$	log-change in the number of non-production employees of industry i from year $t-1$ to year t;
$\Delta\ln MATCOST_{i,t}$	log-change in the deflated cost of materials of industry i from year $t-1$ to year t, deflated using the industry-specific deflator for materials; and
$\Delta\ln ENERGYCOST_{i,t}$	log-change in the deflated cost of energy of industry i from year $t-1$ to year t, deflated using the industry-specific deflator for energy.

production hours (*PRODH*), number of non-production workers (*NPRODE*), cost of materials (*MATCOST*), and cost of energy (*ENERGYCOST*). The variable definitions are presented in Panel B of Table 1.

The NBER-CES data include detailed industry-specific input and output price deflators at the six-digit NAICS level. The output deflator for each six-digit industry is based on the output prices and product mix of that particular industry. The industry-specific materials deflator is based on

American Accounting Association

TABLE 2

Descriptive Statistics

Panel A: Descriptive Statistics for the Firm-Level Compustat Sample

	Mean	Standard Deviation	Median	Lower Quartile	Upper Quartile
Sales revenue (deflated)	$894.82	$4,900.99	$49.46	$8.63	$280.03
SG&A cost (deflated)	$166.24	$706.92	$16.05	$4.38	$63.43
Ratio of SG&A cost to revenue	28.34%	18.40%	24.35%	14.80%	37.77%
COGS (deflated)	$669.29	$3,386.07	$38.25	$7.16	$208.93
Ratio of COGS to revenue	62.59%	18.30%	65.27%	51.19%	76.01%
Number of employees	5.79	20.15	0.54	0.12	2.82
Demand uncertainty $UNCERT_i$	0.35	0.36	0.23	0.15	0.39

Panel B: Descriptive Statistics for the Industry-Level NBER-CES Sample

	Mean	Standard Deviation	Median	Lower Quartile	Upper Quartile
Sales revenue (deflated)	$5,905.16	$13,066.59	$2,935.71	$1,382.55	$5,714.96
Number of employees	35.51	45.62	21.30	11.30	41.50
Payroll (deflated)	$1,171.78	$1,682.81	$645.88	$344.52	$1293.18
Ratio of payroll to revenue	21.40%	9.23%	21.07%	14.92%	27.04%
Number of production workers	26.01	34.11	15.50	8.10	31.20
Number of production hours	51.78	67.68	31.20	16.30	61.80
Number of non-production workers	9.50	14.97	5.00	2.60	10.10
Cost of materials (deflated)	$3,123.21	$7,757.22	$1,417.13	$647.43	$2,907.48
Ratio of cost of materials to revenue	53.50%	36.34%	49.75%	40.30%	60.66%
Cost of energy (deflated)	$125.51	$388.81	$42.96	$19.60	$100.66
Ratio of cost of energy to revenue	2.59%	5.22%	1.34%	0.90%	2.37%
Demand uncertainty $UNCERT_i$	0.11	0.04	0.10	0.08	0.13

prices of 529 inputs and is weighed by the share of each input in industry's input purchases. The industry-specific energy deflator is derived from prices of electricity, residual fuel oil, distillates, coal, coke, and natural gas, and is weighed by the share of each energy type in industry's energy purchases.

We deflate all financial variables using the corresponding industry-specific input or output price deflator. Notably, because the input and output price deflators for each industry are based on prices and quantities relevant for that particular industry, the deflated amounts accurately reflect variation in physical quantities, fully controlling for changes in aggregate price level and changes in relative input and output prices both across and within industries.

In constructing our sample, we discard industry-year observations if current or lagged sales or costs are missing, zero, or negative. To reduce the influence of outliers, we discard 1 percent of extreme values on each tail for the regression variables. The number of industry-year observations in the final sample ranges from 20,109 to 20,744 for different cost categories.

The descriptive statistics are presented in Panel B of Table 2. The average six-digit industry sales revenue is $5,905 million, and the median is $2,936 million, measured in constant 1997 dollars. The average number of industry employees is 35,500, and the median is 21,300. The

average payroll is $1,172 million, or 21.4 percent of sales, and the median is $646 million, or 21.1 percent of sales. The average number of production and non-production employees is 26,000 and 9,500, respectively; the medians are 15,500 and 5,000, respectively. The average number of production hours is 51.78 million, which corresponds to 2,003.4 annual hours per production worker. The cost of materials is on average 53.5 percent of sales; the median is 49.8 percent. The cost of energy is on average 2.6 percent of sales; the median is 1.3 percent.

The industries in the data face substantial demand uncertainty $UNCERT_i$, computed as the standard deviation of log-changes in sales $\Delta lnSALES_{i,t}$ for all valid observations of industry i. The average $UNCERT_i$ is 0.11, and the median is 0.10. Notably, the industry-level demand uncertainty measures are much lower than the firm-level measures from Compustat. This indicates that a large fraction of firm-level variation in sales reflects fluctuations in firms' relative market shares, as opposed to changes in industry-wide sales.

IV. EMPIRICAL RESULTS

Empirical Results for the Firm-Level Compustat Sample

Table 3 presents the estimates for SG&A costs, COGS, and the number of employees. For each cost category, column (a) refers to a simpler model without demand uncertainty, in which the parameter β_2 is set to 0, and the slope on log-change in sales, $\beta_{i,t}$, is equal to $\beta_1 + \gamma_1 controls_{i,t}$. The average estimate of $\beta_1 + \gamma_1 controls_{i,t}$ in this model measures the average short-run response of costs to a 1 percent change in sales, reflecting the average degree of cost rigidity.[23] Column (b) presents the estimates for the full Model A, in which the slope $\beta_{i,t}$ is equal to $\beta_1 + \beta_2 UNCERT_i + \gamma_1 controls_{i,t}$, and the parameter β_2 captures the impact of $UNCERT_i$ on the slope $\beta_{i,t}$, reflecting the relationship between demand uncertainty and cost rigidity.

First, we examine the estimates for the simpler model in column (a). For all three cost categories, the average estimate of the slope $\beta_1 + \gamma_1 controls_{i,t}$ is between 0 and 1, and is significantly different from both 0 and 1. Thus, costs react to changes in sales, but less than proportionately. On average, a 1 percent increase in sales increases SG&A costs by 0.61 percent, COGS by 0.93 percent, and the number of employees by 0.42 percent.

Next, we examine the estimates of the relationship between demand uncertainty and cost rigidity in column (b) of Table 3, where demand uncertainty $UNCERT_i$ is proxied by the standard deviation of log-changes in sales for firm i. For all three cost categories, the estimate $\hat{\beta}_2$ is negative and significant at the 1 percent level. Thus, demand uncertainty reduces the slope $\beta_{i,t} = \beta_1 + \beta_2 UNCERT_i + controls_{i,t}$, resulting in a smaller short-run cost response for the same change in sales. In other words, higher demand uncertainty is associated with a more rigid short-run cost structure, supporting our hypothesis.

The relationship between demand uncertainty and cost rigidity is also economically significant. For example, at the lower quartile of demand uncertainty, the percentage change in costs for a 1 percent change in sales is equal to 0.68 percent for SG&A costs, 0.95 percent for COGS, and 0.55 percent for the number of employees. At the upper quartile of demand uncertainty, the response of costs to a 1 percent change in sales is substantially weaker: 0.57 percent for SG&A costs, a

---

[23] For brevity, in all tables we omit the coefficients on industry dummies in the intercept and in the slope. Instead, we report the average of $\beta_1 + \gamma_1 controls_{i,t}$ based on these coefficients, where the vector $controls_{i,t}$ consists of the industry dummies and GDP growth rate. Technically, the average of $\beta_1 + \gamma_1 controls_{i,t}$ represents a linear combination of the regression coefficients β_1 and γ_1 with known weights, equal to 1 and the sample average of $controls_{i,t}$, respectively. We compute this linear combination and its standard error using the *lincom* command in Stata.

TABLE 3
Estimates of Model A for the Firm-Level Compustat Sample

Model A: $\Delta lnCOST_{i,t} = \beta_0 + \beta_{i,t}\Delta lnSALES_{i,t} + \gamma_0 controls_{i,t} + \varepsilon_{i,t}$,   where $\beta_{i,t} = \beta_1 + \beta_2 UNCERT_i + \gamma_1 controls_{i,t}$.

	Pred. Sign	SG&A Costs		COGS		Total Employees	
		(a)	(b)	(a)	(b)	(a)	(b)
Main Parameters of Interest							
β_2 ($\Delta lnSALES \times UNCERT$)	−		−0.471***		−0.093***		−0.355***
			(−9.16)		(−3.50)		(−18.63)
average $\beta_1 + \gamma_1 controls$ (average slope)	+	0.608***	0.749***	0.929***	0.964***	0.416***	0.599***
		(91.54)	(52.80)	(227.15)	(107.37)	(54.44)	(59.17)
Control Variables in the Slope γ_1							
$\Delta lnSALES \times GDPGROWTH$		0.008***	0.009***	0.001	0.001	−0.002	−0.002
		(2.96)	(3.27)	(0.51)	(0.65)	(−0.50)	(−0.59)
industry dummies IND1,...,IND21		included	included	included	included	included	included
Control Variables in the Intercept γ_0							
GDPGROWTH		0.000	0.000	0.001**	0.000	0.006***	0.004***
		(0.60)	(−0.79)	(2.12)	(1.46)	(10.58)	(8.45)
industry dummies IND1,...,IND21		included	included	included	included	included	included
n		45,990	45,990	51,016	51,016	48,823	48,823
Adjusted R²		0.458	0.462	0.792	0.793	0.274	0.300

*, **, *** Indicate significance at 10, 5, and 1 percent levels, respectively, in two-tailed tests.
The numbers in parentheses are the t-statistics, based on standard errors clustered by firm (Peterson 2009). The average $\beta_1 + \gamma_1 controls$ represents a linear combination of the coefficients β_1 and γ_1 with weights equal to 1 and the average of $controls_{i,t}$, respectively. We compute this linear combination and its t-statistic using the *lincom* command in Stata.

Variable Definitions:
$\Delta lnCOST_{i,t}$ = log-change in deflated costs of firm i from year t−1 to year t;
$\Delta lnSALES_{i,t}$ = log-change in deflated sales of firm i from year t−1 to year t;
$UNCERT_i$ = empirical proxy for demand uncertainty, computed as the standard deviation of $\Delta lnSALES_{i,t}$ for all valid observations of firm i; and
$controls_{i,t}$ = control variables, including three-digit industry dummies $IND1_i,...,IND21_i$ and GDP growth $GDPGROWTH_t$.

reduction of 17 percent, 0.93 percent for COGS, a reduction of 2 percent, and 0.46 percent for the number of employees, a reduction of 16 percent.

In summary, for all three costs categories in our Compustat sample, a higher standard deviation of log-changes in sales is associated with a lower slope $\beta_{i,t}$ in regression of log-changes in costs on log-changes in sales, indicating a positive relationship between demand uncertainty and cost rigidity. This relationship is highly significant both statistically and economically.[24]

Robustness Checks (Not Tabulated)

To control for long-term structural changes, we re-estimate Model A for two shorter periods, 1979–1993 and 1994–2008. For SG&A costs and the number of employees, the estimates of β_2 are negative and significant in both sub-periods, consistent with the results for the full sample period. For COGS, β_2 is negative but insignificant in the first subsample, and negative and significant in the second subsample. Thus, for both time periods, higher demand uncertainty is generally associated with greater cost rigidity. The results also hold when we estimate Model A over three shorter periods, 1979–1989, 1990–2000, and 2001–2008.

We also estimate Model A using the Fama-MacBeth approach (Fama and MacBeth 1973), which is based on aggregation of annual regressions. This approach provides a powerful additional robustness check for long-term structural changes because all the parameters in the underlying annual regressions vary from year to year, directly controlling for long-term changes in cost behavior. The Fama-MacBeth estimates of β_2 are similar in magnitude to our main estimates, negative, and significant. When we examine the underlying annual estimates of β_2, most of them are negative and many are individually significant, even though the sample size in each annual regression is much smaller. For example, for SG&A costs, β_2 is negative in 28 years out of 29, and 20 of those annual estimates are individually significant at the 5 percent level.

In another robustness check, we replace our main measure of demand uncertainty, the standard deviation of log-changes in sales, with an alternative measure that is common in the economics literature, the standard deviation of the *unpredictable* part of log-changes in sales (e.g., McConnell and Perez-Quiros 2000; Blanchard and Simon 2001; Cogley and Sargent 2005; Campbell 2007).[25] The magnitudes and significance levels of the estimates in this robustness check are comparable to our main results. We also use another alternative measure of demand uncertainty, the standard deviation of $\Delta \ln SALES_{i,t}$ of firm i between years $t-4$ to $t-1$. The estimates of β_2 in this specification are negative and significant for all three cost categories, consistent with our main estimates.

Because smaller firms typically face greater demand uncertainty, we also control for firm size using three alternative measures: log-sales of firm i in current year t, log-sales of firm i in prior year $t-1$, and average log-sales of firm i over the sample period. The estimates of β_2 and their significance levels are generally similar to our main estimates.

We also estimate the model after adding controls for cost stickiness (Banker et al. 2014). For all three cost categories, the estimates of β_2 are negative and significant, and their magnitudes are very close to our main estimates. Thus, our findings continue to hold even after controlling for cost stickiness.

---

[24] We also examined the relationship between demand uncertainty and cost rigidity for capital expenditures. Although our theory does not directly apply to long-term investment expenditures, the untabulated empirical results are similar, showing that higher demand uncertainty is associated with greater cost rigidity for capital expenditures. We also get similar results for capital expenditures in the NBER-CES industry-level data.

[25] For each firm i, we first estimate an autoregression model $\Delta \ln SALES_{i,t} = \rho_{0,i} + \rho_{1,i} \Delta \ln SALES_{i,t-1} + v_{i,t}$, where $\rho_{0,i}$ and $\rho_{1,i}$ are firm-specific coefficients, and $v_{i,t}$ is a residual. The term $\rho_{0,i} + \rho_{1,i} \Delta \ln SALES_{i,t-1}$ represents the predicted value of $\Delta \ln SALES_{i,t}$ as of year $t-1$, and $v_{i,t}$ represents the prediction error, i.e., the unpredictable part of log-changes in sales. We then compute $UNCERT_i$ as the standard deviation of the residuals $v_{i,t}$ for firm i.

American
Accounting
Association

In another robustness check, we add control variables from Anderson et al. (2003): asset and employee intensity, computed as the ratio of assets to sales and number of employees to sales, respectively, and lagged log-change in sales. For all three cost categories, the estimates of β_2 are negative and significant, consistent with our main estimates. We also add another set of control variables that capture longer-term factors in cost behavior: firm size, industry-level productivity growth rate, and R&D intensity as a proxy for product complexity. The estimation results are very similar. In another robustness check, we control for long-term sales growth rates, yielding similar results. Since the magnitude of cost response may depend on capacity utilization, we also control for three alternative proxies for capacity utilization, with similar results.[26] Because optimal resource commitments may depend on demand characteristics and technology, we add controls for industry concentration, market share, a proxy for irreversibility of capital investment following Guiso and Parigi (1999), productivity growth, advertising intensity, and R&D intensity. The results are again similar to our main findings. To ensure that our results are not driven by changes in relative prices across six-digit industries, we re-estimate Model A after deflating sales and costs using the corresponding industry-specific deflators from the NBER-CES data. The estimates are consistent with our main findings. The results also continue to hold when we replace annual log-changes in costs and sales with longer-term log-changes over two, three, and four years. Notably, for all cost categories, the proportion of variable costs increases significantly with the aggregation period, supporting the notion that costs appear more variable in the long run, as discussed in footnote 2. For example, when concurrent sales rise by 1 percent, SG&A costs rise by 0.61 percent on average in annual data, as documented in Table 3, but rise by 0.78 percent in untabulated results for a four-year aggregation period.

To allow for further heterogeneity in cost behavior, we estimate a model with firm-specific random coefficients on log-change in sales and its interaction with demand uncertainty, and an additional model in which random coefficients vary both across firms and over time. The estimates in both models are similar to our main results.

We also estimate Model A separately for each of the 21 three-digit NAICS industries in the data. These estimates of β_2 are less precise, due to much smaller sample sizes, and for many industries the estimate of β_2 is insignificant. However, among the three-digit industries with statistically significant estimates of β_2, representing 12 industries for SG&A costs, 3 industries for COGS, and 18 industries for the number of employees, all $\hat{\beta}_2$'s have the expected sign. When we combine the industry-specific estimates using the Fama-MacBeth approach, the combined estimate of β_2 is negative and significant. This further supports our main empirical findings, that higher demand uncertainty is associated with greater cost rigidity.

As an additional indirect test, we examine the relationship between demand uncertainty and inventories. Similar to higher committed capacity, higher inventory levels allow firms to cope better with volatile demand. Therefore, firms facing greater demand uncertainty are likely to maintain higher inventory levels, along with higher committed capacity. As expected, higher demand uncertainty is associated with a significantly higher ratio of inventories to COGS, both with and without controls for industry and GDP growth, suggesting that firms use higher inventories as a complementary mechanism for dealing with demand uncertainty.

---

[26] One proxy is industry-level capacity utilization from the Federal Reserve, available at: http://www.federalreserve.gov/releases/g17/caputl.htm. The two other proxies are based on changes in firm size, measured as log-change in total assets and log-change in net PP&E.

Empirical Results for the Industry-Level NBER-CES Sample

Table 4 presents the estimates for the seven cost categories in the NBER-CES industry-level data: number of employees, payroll, number of production workers, number of non-production workers, number of production hours, cost of materials, and cost of energy.

First we examine the estimates for a simpler model without demand uncertainty, presented in column (a). The slope on log-changes in sales in this model, $\beta_{i,t} = \beta_1 + \gamma_1 controls_{i,t}$, reflects the percentage change in costs for a 1 percent change in sales, and characterizes the degree of cost rigidity. For all seven cost categories, the average estimate of the slope $\beta_{i,t}$ is between 0 and 1, and is significantly different from both 0 and 1. Thus, costs react to changes in sales, but less than proportionately. On average, when sales increase by 1 percent, the number of employees increases by 0.53 percent, payroll by 0.59 percent, the number of production workers by 0.56 percent, the number of non-production workers by 0.44 percent, production hours by 0.59 percent, the cost of materials by 0.88 percent, and the cost of energy by 0.43 percent. The relative magnitudes of these estimates are consistent with prior expectations. For example, the number of production hours, which can be changed at short notice with minimal adjustment costs, is more sensitive to sales changes than is the number of production workers. The least rigid cost category is the cost of materials, which changes by 0.88 percent for a 1 percent change in sales.

Next, we examine the relationship between demand uncertainty and cost rigidity, where demand uncertainty is proxied by the standard deviation of log-changes in sales for industry i, $UNCERT_i$. This relationship is captured by the estimates of β_2 in column (b) of Table 4. The estimate $\hat{\beta}_2$ is negative and significant at the 1 percent level for the number of employees, payroll, production workers, non-production workers, production hours, and cost of energy. Thus, as expected, higher demand uncertainty for these cost categories is associated with a lower slope on log-changes in sales, $\beta_{i,t} = \beta_1 + \beta_2 UNCERT + \gamma_1 controls_{i,t}$, indicating a more rigid short-run cost structure. One distinct cost category is the cost of materials. We do not expect demand uncertainty to have a significant effect for materials, unlike all other cost categories in the data, since uncertainty for materials can be dealt with via inventories. As expected, the estimate $\hat{\beta}_2$ for materials is close to 0 and is insignificant even at the 10 percent level.

The impact of demand uncertainty on cost behavior is also economically significant. For the five labor cost variables in the data, the response of costs to a 1 percent change in sales, measured using the slope $\beta_{i,t}$, is 7.4–9.9 percent weaker for an industry at the top quartile of demand uncertainty than for an industry at the bottom quartile; for the cost of energy, it is 16.5 percent weaker.

In summary, for all cost categories except materials, higher demand uncertainty, measured using the standard deviation of log-changes in sales for industry i, is associated with greater cost rigidity, i.e., a lower slope $\beta_{i,t}$ in regression of log-changes in costs on log-changes in sales. This relationship is significant both statistically and economically for all cost categories except materials, where we do not expect a significant effect.

Robustness Checks

We conduct all of the robustness checks described earlier for the Compustat sample, including estimation over shorter time periods and Fama-MacBeth estimation to control for long-term structural changes, estimation for alternative measures of demand uncertainty, inclusion of additional control variables, random-coefficients estimation, and industry-by-industry estimation. The results in all of these robustness checks generally support our main findings. For all cost categories except materials, the estimates of β_2 are negative, and most of them are significant at the 5 percent level, indicating that demand uncertainty is associated with greater cost rigidity. For materials, the estimates of β_2 in all of the robustness checks are close to 0 and insignificant, as

TABLE 4

Estimates of Model A for the Industry-Level NBER-CES Sample

Model A: $\Delta lnCOST_{i,t} = \beta_0 + \beta_{i,t}\Delta lnSALES_{i,t} + \gamma_0 controls_{i,t} + \varepsilon_{i,t}$, where $\beta_{i,t} = \beta_1 + \beta_2 UNCERT_i + \gamma_1 controls_{i,t}$.

Panel A: Estimates for Total Employees, Total Payroll, and Production Workers

	Pred. Sign	Total Employees		Total Payroll		Production Workers	
		(a)	(b)	(a)	(b)	(a)	(b)
Main Parameters of Interest							
β_2 ($\Delta lnSALES \times UNCERT$)	−		−0.987***		−0.992***		−0.962***
			(−4.09)		(−4.69)		(−3.82)
average $\beta_1 + \gamma_1 controls$ (average slope)	+	0.533***	0.648***	0.590***	0.706***	0.560***	0.673***
		(69.44)	(24.01)	(82.14)	(29.63)	(70.97)	(23.62)
Control Variables in the Slope γ_1							
$\Delta lnSALES \times GDPGROWTH$		0.006***	0.006***	0.007***	0.008***	0.003	0.004
		(2.79)	(2.90)	(3.52)	(3.63)	(1.34)	(1.44)
industry dummies *IND1,...,IND21*		included	included	included	included	included	included
Control Variables in the Intercept γ_0							
GDPGROWTH		−0.024***	−0.023***	−0.031***	−0.031***	0.035***	0.035***
		(−8.52)	(−8.52)	(−12.84)	(−12.91)	(−12.48)	(−12.45)
industry dummies *IND1,...,IND21*		included	included	included	included	included	included
n		20,671	20,671	20,698	20,698	20,671	20,671
Adjusted R²		0.479	0.481	0.591	0.593	0.477	0.478

TABLE 4 (continued)

Panel B: Estimates for Non-Production Employees, Production Hours, Cost of Materials, and Cost of Energy

	Pred. Sign	Non-Production Employees		Production Hours		Cost of Materials		Cost of Energy	
		(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
Main Parameters of Interest									
β_2 ($\Delta lnSALES \times UNCERT$)	−		−0.914***		−0.907***		−0.227		−1.582***
			(−3.15)		(−3.73)		(−1.00)		(−7.28)
average $\beta_1 + \gamma_1 controls$ (average slope)	+	0.436***	0.543***	0.592***	0.697***	0.878***	0.904***	0.430***	0.615***
		(43.76)	(16.02)	(74.37)	(25.32)	(114.16)	(34.55)	(42.48)	(23.60)
Control Variables in the Slope γ_1									
$\Delta lnSALES \times GDPGROWTH$		0.009***	0.009***	0.002	0.003	0.007***	0.007***	0.005	0.005
		(2.86)	(2.96)	(0.87)	(0.98)	(3.07)	(3.08)	(1.46)	(1.60)
industry dummies $IND1,\ldots,IND21$		included	included	included	included	included	included	included	included
Control Variables in the Intercept γ_0									
$GDPGROWTH$		0.009***	0.009***	−0.040***	−0.040***	−0.012***	−0.011***	0.000	0.000
		(3.01)	(3.11)	(−13.77)	(−13.75)	(−5.51)	(−5.49)	(−0.02)	(0.08)
industry dummies $IND1,\ldots,IND21$		included	included	included	included	included	included	included	included
n		20,109	20,109	20,676	20,676	20,744	20,744	20,575	20,575
Adjusted R^2		0.176	0.177	0.508	0.509	0.660	0.660	0.180	0.183

*, **, *** Indicate significance at 10, 5, and 1 percent levels, respectively, in two-tailed tests.
The numbers in parentheses are the t-statistics, based on standard errors clustered by six-digit industry (Peterson 2009). The average $\beta_1 + \gamma_1 controls$ represents a linear combination of the coefficients β_1 and γ_1 with weights equal to 1 and the average of $controls_{i,t}$, respectively. We compute this linear combination and its t-statistic using the *lincom* command in Stata.

Variable Definitions:
$\Delta lnCOST_{i,t}$ = log-change in deflated costs of six-digit industry i from year $t-1$ to year t;
$\Delta lnSALES_{i,t}$ = log-change in deflated sales of six-digit industry i from year $t-1$ to year t;
$UNCERT_i$ = empirical proxy for demand uncertainty, computed as the standard deviation of $\Delta lnSALES_{i,t}$ for all valid observations of six-digit industry i; and
$controls_{i,t}$ = control variables, including three-digit industry dummies $IND1_i,\ldots,IND21_i$ and GDP growth $GDPGROWTH_t$.

expected. In a supplementary indirect test, we also document that higher demand uncertainty is associated with a significantly higher ratio of inventories to sales, indicating that, along with increased capacity, increased inventory serves as a complementary mechanism for dealing with demand uncertainty.

V. CONCLUDING REMARKS

We examine the relationship between demand uncertainty and cost rigidity analytically and empirically. We hypothesize that in the presence of significant congestion costs, greater demand uncertainty should lead firms to increase their capacity commitments of fixed activity resources, resulting in a *more* rigid short-run cost structure with higher fixed and lower variable costs. We formalize this argument in a simple analytical model of optimal capacity choice under uncertainty.

Our empirical analysis uses firm-level data from Compustat and industry-level data from the NBER-CES Manufacturing Industry Database. In agreement with our hypothesis, greater demand uncertainty, proxied by the standard deviation of log-changes in sales, is associated with greater cost rigidity, i.e., a lower slope in a regression of log-changes in costs on contemporaneous log-changes in sales. These results are robust for multiple measures of costs, both in the firm-level sample from Compustat and in the industry-level sample from the NBER-CES Industry Database.

While we document that empirical data are overall consistent with increased demand uncertainty leading to a more rigid cost structure, the conventional wisdom favors adopting a more variable cost structure. This prescription may be warranted in a related, but qualitatively different, context featuring greater *downside risk*, i.e., an increase in the likelihood of unfavorable realizations without a commensurate increase in the likelihood of favorable realizations. Greater downside risk means that the *mean* of demand decreases, since only unfavorable demand realizations become more likely. Thus, in the case of increased downside risk, managers' capacity choices will reflect the combined impact of the increased variance and the decreased mean. By contrast, in the case of increased demand uncertainty, the variance of demand increases while the mean remains unchanged, as illustrated in Figure 1.

This potential confusion between uncertainty and downside risk is important because these two phenomena have dramatically different implications for the optimal choice of capacity levels and, consequently, for the short-run cost structure. Proposition 1 shows that given our assumptions about congestion costs, increased demand uncertainty leads to a higher optimal level of the fixed input and a more rigid short-run cost structure with higher fixed and lower variable costs. By contrast, if we increase the *downside risk* in the same model, meaning that the likelihood of highly unfavorable demand realizations increases whereas the likelihood of favorable demand realizations remains unchanged, the predictions are reversed. The optimal level of the fixed input will decrease, leading to a *less rigid* short-run cost structure with lower fixed and higher variable costs. Thus, the conventional wisdom and consultants' advice to shift from fixed to variable costs fit the case of increased *downside risk* but not the case of increased *demand uncertainty*.

Additionally, while we focus on the fundamental trade-off between fixed and variable inputs, consultants' prescriptions are often confined to a few specific ways to "variabilize" the cost structure, such as outsourcing and short-term leases of fixed assets. However, even when such solutions are desirable, they may be desirable for reasons such as greater downside risk rather than greater demand uncertainty, consistent with our empirical findings that greater uncertainty does not imply greater variability of costs.

Another important caveat is that consultants' prescriptions involve risk-shifting from the firm onto its suppliers. When demand uncertainty increases, suppliers have to be compensated for the added risk in the form of higher prices that incorporate a risk premium. Further, if the firm has a greater ability to bear risk than its suppliers, the risk premium will go up disproportionately. This

will lead the firm to *reduce* its reliance on "variabilization" solutions, resulting in a more rigid short-run cost structure. Future research will examine whether and under what circumstances these alternative methods provide a good solution for increased uncertainty.[27]

In this study, we have used broad-based large-sample analysis, which is the most common approach in cost behavior studies in accounting. Another fruitful complementary approach for future research would be to conduct detailed industry case studies, leveraging the unique technical and institutional details of a specific industry to gain better insight into the relationship between uncertainty and cost structure, as well as alternative ways to cope with increased demand uncertainty. This could include studies of industries before and after they experienced exogenous shocks that changed the level of uncertainty. However, an important limitation of such industry-specific studies based on unique natural experiments is limited generalizability of the findings.

REFERENCES

Abel, A. 1983. Optimal investment under uncertainty. *American Economic Review* 73 (1): 228–233.

Abel, A., and J. Eberly. 1994. A unified model of investment under uncertainty. *American Economic Review* 84 (1): 1369–1384.

Anderson, M. C., R. D. Banker, and S. N. Janakiraman. 2003. Are selling, general, and administrative costs "sticky"? *Journal of Accounting Research* 41 (1): 47–63.

Arya, A., and J. Glover. 2001. Option value to waiting created by a control problem. *Journal of Accounting Research* 39 (3): 405–415.

Balakrishnan, R., K. Sivaramakrishnan, and G. Sprinkle. 2008. *Managerial Accounting*. Hoboken, NJ: John Wiley & Sons.

Banker, R. D., S. Datar, and S. Kekre. 1988. Relevant costs, congestion and stochasticity in production environments. *Journal of Accounting and Economics* 10 (3): 171–198.

Banker, R. D., and H. H. Johnston. 1993. An empirical study of cost drivers in the U.S. airline industry. *The Accounting Review* 68 (3): 576–601.

Banker, R. D., G. Potter, and R. G. Schroeder. 1995. An empirical analysis of manufacturing overhead cost drivers. *Journal of Accounting and Economics* 19 (1): 115–137.

Banker, R. D., and D. Byzalov. 2013. *Asymmetric Cost Behavior*. Working paper, Temple University.

Banker, R. D., D. Byzalov, M. Ciftci, and R. Mashruwala. 2014. The moderating effect of prior sales changes on asymmetric cost behavior. *Journal of Management Accounting Research* (forthcoming).

Bartelsman, E. J., and W. B. Gray. 1996. *The NBER manufacturing productivity database*. Working paper, National Bureau of Economic Research.

Blanchard, O., and J. Simon. 2001. The long and large decline in U.S. output volatility. *Brookings Papers on Economic Activity* 1: 135–164.

Caballero, R. J. 1991. On the sign of the investment-uncertainty relationship. *American Economic Review* 81 (1): 279–288.

Campbell, S. D. 2007. Macroeconomic volatility, predictability, and uncertainty in the great moderation: Evidence from the survey of professional forecasters. *Journal of Business & Economic Statistics* 25 (2): 191–200.

---

[27] Another factor that may affect managerial decisions is loss aversion (Kahneman and Tversky 1984). A more rigid cost structure leads to increased profits for high demand realizations and increased losses for low demand realizations. Under loss aversion, managers weigh losses more heavily than gains, which may lead them to prefer a less rigid cost structure. Further, this effect is likely to be stronger for firms that are more likely to incur losses, which includes firms facing greater demand uncertainty and firms with lower average profitability. However, our empirical results, including robustness checks with controls for industry concentration and other determinants of average firm profitability, suggest that loss aversion does not play a dominant role in the relationship between demand uncertainty and cost structure.

American Accounting Association

Chen, C. X., H. Lu, and T. Sougiannis. 2012. The agency problem, corporate governance, and the behavior of selling, general, and administrative costs. *Contemporary Accounting Research* 29 (1): 252–282.

Cogley, T., and T. J. Sargent. 2005. Drifts and volatilities: Monetary policies and outcomes in the post WWII U.S. *Review of Economic Dynamics* 8 (2): 262–302.

Comin, D., and T. Philippon. 2005. The rise in firm-level volatility: Causes and consequences. *NBER Macroeconomics Annual* 20: 167–201.

Comin, D., and S. Mulani. 2006. Diverging trends in aggregate and firm volatility. *Review of Economics and Statistics* 88 (2): 374–383.

Cooper, R., and R. S. Kaplan. 1987. How cost accounting systematically distorts product costs. In *Accounting and Management: Field Study Perspectives*, edited by W. J. Bruns, and R. S. Kaplan, 204–228. Boston, MA: Harvard Business School Press.

Cooper, R., and R. S. Kaplan. 1992. Activity-based systems: Measuring the costs of resource usage. *Accounting Horizons* (September): 1–13.

Christensen, L. R., D. W. Jorgenson, and L. J. Lau. 1973. Transcendental logarithmic production frontiers. *The Review of Economics and Statistics* 55 (1): 28–45.

Datar, S. M., S. Kekre, T. Mukhopadhyay, and K. Srinivasan. 1993. Simultaneous estimation of cost drivers. *The Accounting Review* 68 (3): 602–614.

Davidson, R., and J. MacKinnon. 1981. Several tests for model specification in the presence of alternative hypotheses. *Econometrica* 49: 781–793.

Davis, S., and J. Kahn. 2008. Interpreting the great moderation: Changes in the volatility of economic activity at the macro and micro levels. *Journal of Economic Perspectives* 22 (4): 155–180.

Dechow, P. M., and I. D. Dichev. 2002. The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review* 77 (Supplement): 35–59.

DeGroot, M., and M. Schervish. 2002. *Probability and Statistics*. Boston, MA: Addison-Wesley.

Dichev, I. D., and V. W. Tang. 2009. Earnings volatility and earnings predictability. *Journal of Accounting and Economics* 47 (1): 160–181.

Dierynck, B., W. R. Landsman, and A. Renders. 2012. Do managerial incentives drive cost behavior? Evidence about the role of the zero earnings benchmark for labor cost behavior in private Belgian firms. *The Accounting Review* 87 (4): 1219–1246.

Dixit, A. K., and R. S. Pindyck. 1994. *Investment under Uncertainty*. Princeton, NJ: Princeton University Press.

Fama, E. F., and J. D. MacBeth. 1973. Risk, return and equilibrium: Empirical tests. *Journal of Political Economy* 81 (3): 607–636.

Foster, G., and M. Gupta. 1990. Manufacturing overhead cost driver analysis. *Journal of Accounting and Economics* 12 (1): 309–337.

Guiso, L., and G. Parigi. 1999. Investment and demand uncertainty. *The Quarterly Journal of Economics* 114 (1): 185–227.

Hartman, R. 1972. The effects of price and cost uncertainty on investment. *Journal of Economic Theory* 5 (2): 258–266.

Kahneman, D., and A. Tversky. 1984. Choices, values and frames. *American Psychologist* 39 (4): 341–350.

Kallapur, S., and L. Eldenburg. 2005. Uncertainty, real options, and cost behavior: Evidence from Washington State hospitals. *Journal of Accounting Research* 43 (5): 735–752.

Kama, I., and D. Weiss. 2013. Do earnings targets and managerial incentives affect sticky costs? *Journal of Accounting Research* 51 (1): 201–224.

Kothari, S. P., T. E. Laguerre, and A. J. Leone. 2002. Capitalization versus expensing: Evidence on the uncertainty of future earnings from capital expenditures versus R&D outlays. *Review of Accounting Studies* 7 (4): 355–382.

Mao, J. C. 1970. Survey of capital budgeting: Theory and practice. *Journal of Finance* 25 (2): 349–360.

March, J. G., and Z. Shapira. 1987. Managerial perspectives on risk and risk taking. *Management Science* 33 (11): 1404–1418.

Mauer, D. C., and S. H. Ott. 1995. Investment under uncertainty: The case of investment replacement decisions. *Journal of Financial and Quantitative Analysis* 30 (4): 581–605.

McConnell, M., and G. Perez-Quiros. 2000. U.S. output fluctuations in the United States: What has changed since the early 1950s. *American Economic Review* 90 (5): 1464–1476.

McDonald, R. L., and D. R. Siegel. 1985. Investment and the valuation of firms when there is an option to shut down. *International Economic Review* 26 (2): 331–349.

McDonald, R. L., and D. R. Siegel. 1986. The value of waiting to invest. *Quarterly Journal of Economics* 101 (4): 707–727.

Miller, J., and T. Vollman. 1985. The hidden factory. *Harvard Business Review* 63 (5): 142–150.

Noreen, E., and N. Soderstrom. 1994. Are overhead costs strictly proportional to activity? Evidence from hospital departments. *Journal of Accounting and Economics* 17 (1): 255–278.

Noreen, E., and N. Soderstrom. 1997. The accuracy of proportional cost models: Evidence from hospital service departments. *Review of Accounting Studies* 2 (1): 89–114.

Peterson, M. A. 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies* 22 (1): 435–480.

Pindyck, R. S. 1988. Irreversible investment, capacity choice, and the value of the firm. *American Economic Review* 78 (5): 969–985.

Stock, J. H., and M. W. Watson. 2002. Has the business cycle changed and why? *NBER Macroeconomics Annual* 17: 159–218.

Weiss, D. 2010. Cost behavior and analysts' earnings forecasts. *The Accounting Review* 85 (4): 1441–1471.

Wooldridge, J. M. 2002. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.

Zhang, X. F. 2006. Information uncertainty and stock returns. *The Journal of Finance* 61 (1): 105–137.

APPENDIX A
Derivations for the Analytical Model

Preliminary Derivations

The production function $f(x, z)$ has the standard properties: $f_x > 0, f_z > 0$, positive marginal product; $f_{xx} < 0, f_{zz} < 0$, diminishing marginal product; $f_{xz} > 0$, complementarity between the two inputs. f_x, f_z and f_{xx}, f_{xz}, f_{zz} denote first and second partial derivatives of $f(x, z)$, respectively.

Through differentiation of implicit function (3), the first partial derivatives of $z^*(q|x)$ are:

$$\frac{\partial z^*(q|x)}{\partial q} = \frac{1}{f_z\left(z^*(q|x)\right)} > 0. \tag{11}$$

$$\frac{\partial z^*(q|x)}{\partial x} = \frac{f_x\left(z^*(q|x)\right)}{f_z\left(z^*(q|x)\right)} < 0. \tag{12}$$

The second partial derivatives of $z^*(q|x)$, obtained by differentiating (11) and (12), are:

$$\frac{\partial^2 z^*(q|x)}{\partial q^2} = -\frac{f_{zz}}{f_z^3} > 0. \tag{13}$$

$$\frac{\partial^2 z^*(q|x)}{\partial q \partial x} = \frac{f_x f_{zz} - f_{xz} f_z}{f_z^3} < 0. \tag{14}$$

$$\frac{\partial^2 z^*(q|x)}{\partial x^2} = -\frac{f_{xx} f_z - 2 f_{xz} f_x + f_{zz} f_x \frac{f_x}{f_z}}{f_z^2} > 0. \tag{15}$$

From (4), the marginal cost is:

$$mc(q|\ x) \equiv \frac{\partial C(q|\ x)}{\partial q} = p_z \frac{\partial z^*(q|\ x)}{\partial q} > 0. \tag{16}$$

Properties of the Cost Function

Lemma 1: Conditional on q, the marginal cost $mc(q|x)$ is decreasing in x.

Proof

From (16), the derivative $\partial mc(q|\ x)/\partial x$ is equal to:

$$\frac{\partial mc(q|\ x)}{\partial x} = p_z \frac{\partial^2 z^*(q|\ x)}{\partial q \partial x}, \tag{17}$$

where: $p_z > 0$, and $\frac{\partial^2 z^*(q|\ x)}{\partial q \partial x} < 0$ from (14). Therefore, $\partial mc(q|\ x)/\partial x < 0$, i.e., the marginal cost is decreasing in x.∎

Lemma 2: Conditional on x, the marginal cost $mc(q|x)$ is increasing in q, i.e., the cost function $C(q|x)$ is convex in q.

Proof

From (16), the derivative $\partial mc(q|\ x)/\partial q$ is equal to:

$$\frac{\partial mc(q|\ x)}{\partial q} = p_z \frac{\partial^2 z^*(q|\ x)}{\partial q^2}, \tag{18}$$

where $p_z > 0$, and $\frac{\partial^2 z^*(q|\ x)}{\partial q^2} > 0$ from (13). Therefore, $\partial mc(q|\ x)/\partial q$ is positive, i.e., the marginal cost is increasing in q.

Because $\partial mc(q|\ x)/\partial q$ corresponds to the second derivative of the total cost function $C(q|x)$ with respect to q, $\partial mc(q|\ x)/\partial q > 0$ implies that $C(q)$ is convex in q.∎

Sufficient Conditions for a Positive Relationship between σ and x

We formulate the sufficient conditions in terms of the output elasticities $\eta_x \equiv \partial \ln f(x,z)/\partial \ln x$ and $\eta_z \equiv \partial \ln f(x,z)/\partial \ln z$.

Proposition 1: Demand Uncertainty and the Optimal Choice of the Fixed Input: If the production function (2) satisfies the following conditions for output elasticities everywhere in the relevant range:

(1) $0 < \eta_x < 1, 0 < \eta_z < 1$;

(2) η_x, η_z are non-increasing in x and z, respectively, holding the other input constant (i.e., in production function (2), $\beta_{11} \leq 0, \beta_{22} \leq 0$); and

(3) η_x is non-decreasing in z and η_z is non-decreasing in x (i.e., $\beta_{12} \geq 0$), then the optimal level of the fixed input x is increasing in demand uncertainty σ.

Proof

First, we establish that under conditions (1)–(3), the term $\frac{\partial z^*(q|\ x)}{\partial x}$ on the right-hand side of (7) is concave in q. From (14), the second derivative of $\frac{\partial z^*(q|\ x)}{\partial x}$ with respect to q is:

$$\frac{\partial^3 z^*(q \mid x)}{\partial x \partial q^2} = \frac{3 f_z f_{xz} f_{zz} - 3 f_x f_{zz}^2 + f_x f_z f_{zzz} - f_z^2 f_{xzz}}{f_z^5}. \tag{19}$$

Since the denominator f_z^5 is positive, this derivative is negative (i.e., $\frac{\partial z^*(q \mid x)}{\partial x}$ is concave with respect to q) if the numerator is negative:

$$3 f_z f_{xz} f_{zz} - 3 f_x f_{zz}^2 + f_x f_z f_{zzz} - f_z^2 f_{xzz} < 0. \tag{20}$$

After rewriting the partial derivatives of the production function (2) in terms of output elasticities and simplifying, this inequality can be rewritten as:

$$\eta_x \eta_z^3 - (1 + \beta_{22}) \eta_x \eta_z^2 + \beta_{12} \eta_z^3 - 2\beta_{12} \eta_z^2 + 3\beta_{12} \beta_{22} \eta_z - 3\beta_{22}^2 \eta_x + 3\beta_{22} \eta_x \eta_z < 0. \tag{21}$$

This condition is satisfied under conditions (1)–(3). Specifically, after re-arranging, we can characterize the sign of (21) as follows:

$$
\begin{array}{ll}
(\eta_x \eta_z^3 - \eta_x \eta_z^2) + & (\text{strictly negative}: \eta_x, \eta_z \in (0,1), \text{ so } \eta_x \eta_z^2 > \eta_x \eta_z^3); \\
+\beta_{12}(\eta_z^3 - 2\eta_z^2) + & (\text{negative or } 0: \beta_{12} \geq 0, \text{ and } \eta_z \in (0,1), \text{ so } \eta_z^2 > \eta_z^3); \\
+3\beta_{12}\beta_{22}\eta_z + & (\text{negative or } 0: \beta_{12} \geq 0, \beta_{22} \leq 0, \text{ and } \eta_z > 0); \\
+(-3\beta_{22}^2 \eta_x) + & (\text{negative or } 0: \eta_x > 0); \text{ and} \\
+\beta_{22}(3\eta_x \eta_z - \eta_x \eta_z^2) & (\text{negative or } 0: \beta_{22} \leq 0, \text{ and } \eta_x, \eta_z \in (0,1), \text{ so } \eta_x \eta_z > \eta_x \eta_z^2).
\end{array}
$$

Since the first term is strictly negative, and all other terms are weakly negative, condition (21) is satisfied. Consequently, $\frac{\partial z^*(q \mid x)}{\partial x}$ is concave with respect to q.

Due to Jensen's inequality, the concavity of $\frac{\partial z^*(q \mid x)}{\partial x}$ implies that when demand uncertainty σ increases, the expectation $E\left[\frac{\partial z^*(q \mid x)}{\partial x}\right]$ on the right-hand side of the first order condition (7) decreases. To offset this decrease and to restore condition (7) to equality, the fixed input x has to increase, because $\frac{\partial z^*(q \mid x)}{\partial x}$ is increasing in x as shown in (15). Consequently, the optimal level of the fixed input x is increasing in demand uncertainty σ. ∎

Supplementary Analysis: Effect of Increased Downside Risk

Corollary 1: An increase in downside risk reduces the optimal level of the fixed input x.

Proof

The optimal level of the fixed input x is determined by the first-order condition (7):

$$p_x = -p_z E_q \left[\frac{\partial z^*(q \mid x)}{\partial x}\right],$$

where, based on (14) and (15), $\partial z^*/\partial x$ is decreasing in q and increasing in x, respectively.

Since $\partial z^*/\partial x$ is decreasing in q, it has a higher value for unfavorable realizations of q than for favorable realizations. An increase in downside risk shifts the weight in the probability distribution of q to highly unfavorable realizations, for which $\partial z^*/\partial x$ is higher, and away from favorable and moderately unfavorable realizations, for which $\partial z^*/\partial x$ is lower. Therefore, the expectation $E_q[\partial z^*/\partial x]$ in (7) will increase. To return the first-order condition (7) to equality, the optimal level of x has to decrease. In particular, because $\partial z^*/\partial x$ is increasing in x, a decrease in x will offset the positive impact of increased downside risk on $E_q[\partial z^*/\partial x]$, restoring condition (7) to equality. Consequently, greater downside risk reduces the optimal level of the fixed input x. ∎

American Accounting Association