The Managerial Perception of Uncertainty and Cost Behavior

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Abstract

Extensive theoretical research demonstrates the pivotal role uncertainty and its components play in shaping a firm's cost behavior. Our study contributes to this literature by conducting a comprehensive analysis of the inherent tension between the effects of price and demand uncertainty on cost elasticity and cost asymmetry. Using the occurrence of words implying uncertainty in forward-looking statements in the Management Discussion and Analysis section of 10-K reports to measure the managerial perception of the overall, price, and demand uncertainty, we provide evidence of a positive and significant association between price uncertainty and cost elasticity and a negative and significant association between demand uncertainty and cost elasticity. The former finding is consistent with managers' desire to shift to a more elastic cost function in the face of high price uncertainty; the latter supports the hypothesis that firms facing demand uncertainty will increase their capacity of fixed resources to avoid disproportionately large production congestion costs associated with high demand realizations. We also document that managerial perception of the overall uncertainty exacerbates the degree of cost asymmetry. Our empirical evidence supports the theoretical argument that the managerial perception of uncertainty and its components influences their resource allocation decisions, and suggests that any analysis of the relation between uncertainty and a firm's cost behavior needs to be conducted in the context of a specific type of uncertainty as well as other economic drivers.

1. Introduction

Prior research has examined the impact of uncertainty on firms' cost behavior and on managers' operating decisions (for example, McDonald and Siegel, 1985, 1986; Dixit and Pindyck, 1994; Arya and Glover, 2001; Banker et al., 2014). This research argues that uncertainty is an important determinant of firms' cost behavior and analytically demonstrates that managers will shift to a more elastic cost function in the face of high price uncertainty, but are likely to choose a less elastic cost function in the face of high demand uncertainty. Uncertainty has also been suggested as one of the drivers of asymmetric cost behavior.[1] Specifically, Anderson, Banker, and Janakiraman (ABJ, 2003) propose that when managers face demand uncertainty they might make a deliberate decision to maintain unused resources when current demand falls until the uncertainty is resolved. They do so to minimize both current and future adjustment costs associated with reducing or restoring resources.

Notwithstanding the fundamental role of the managerial perception of uncertainty in determining a firm's cost behavior in the theoretical literature, the empirical evidence on this relation arises from a handful of studies.[2] The analyses in these studies focus on different elements of uncertainty (e.g., profit margin or demand), is conducted in specific industries (primarily hospitals), are mostly related to event-driven uncertainty (a change in price regulations or elections), and ultimately provide a somewhat limited evidence regarding the tension between the effects of various types of uncertainty on cost elasticity and cost asymmetry. Importantly, while

[1] Costs are said to behave asymmetrically when they increase, on average, differently when current sales rise than they decrease when current sales fall by an equivalent amount. Banker and Byzalov (2014) provide a review of this literature.
[2] These studies are Kallapur and Eldenburg (2005), Banker, Byzalov, and Plehn-Dujowich (2014b), Holzhacker, Krishnan, and Mahlendorf (2015a, 2015b), and Lee, Pittman, and Saffar (2016). See the detailed discussion of these studies in Section 2.

prior studies generally consider the individual effect of each uncertainty type, they generally do not analyze the potential effects of interactions between different types of uncertainty and firm cost behavior. Accordingly, empirical evidence on the general and contextual impact of uncertainty on the sign and magnitude of cost elasticity and the degree of cost asymmetry remains limited and somewhat inconclusive.

The objective of the present study is to extend this literature by providing a comprehensive, large-sample empirical analysis of the ongoing, inherent effects of the managerial perception of demand and price uncertainty on cost elasticity and cost asymmetry.[3] Specifically, we ask the following research questions: (i) How does the managerial perception of demand and price uncertainty impact cost elasticity? (ii) How does the managerial perception of uncertainty and its components affect the degree of cost asymmetry? (iii) Does the effect of uncertainty on cost asymmetry depend on the amount of unused resources available to managers at the beginning of the period?

Analyzing the relation between uncertainty and its components and cost behavior is important because costs directly impact earnings. Moreover, the evidence in prior studies indicates that the understanding of a firm's cost behavior provides new insights on financial accounting topics, such as predicting future earnings, analyzing the properties of analyst earnings forecasts, and conducting financial statement analysis (e.g., Banker and Chen 2006; Weiss, 2010; Banker et al., 2016; Homburg et al., 2018).

We begin our analysis by examining empirically the effect of the individual and incremental managerial perception of price and demand uncertainty on cost elasticity. Theoretical

[3]Price uncertainty refers to the uncertainty regarding the output price relative to the variable cost of production (i.e., the contribution margin). Demand uncertainty refers to the variability of the physical volume to be produced (see additional discussion in Section 2).

models argue that price and demand uncertainty have opposite effects on the degree of cost elasticity. Specifically, McDonald and Siegel (1985) suggest that managers choose a more elastic cost function in the face of increased uncertainty in output price to provide the flexibility to respond to changes in economic conditions. This flexibility becomes more valuable as uncertainty increases. Banker et al. (2014b) provide a theoretical model indicating that volume uncertainty leads managers to make resource commitment decisions that reduce elasticity due to the concern of resource congestion costs in high realizations of demand. We test the predictions of these theoretical models by constructing firm-specific and time-varying empirical measures of the managerial perception of the overall uncertainty as well as its decomposition into price and demand uncertainty. These empirical measures are based on the occurrence of uncertainty-related words in forward-looking statements (FLS) made in the *Management Discussion and Analysis* section (MD&A) of 10-K reports.[4] Consistent with the predictions in the theoretical models, we document a *positive* and significant association between our measure of price uncertainty and cost elasticity and a *negative* and significant association between our measure of demand uncertainty and cost elasticity.[5] We further show that this negative relation prevails only when price uncertainty is moderate to low, but is insignificant when the managerial perception of price uncertainty is higher. Interestingly, we document that the degree of elasticity is statistically the same when both price and demand uncertainty are either extremely high or extremely low. This finding supports the theory of the opposing impact of price and demand uncertainty on elasticity and suggests that their confounding impact is of similar magnitude when both are at their highest

[4] FLS provide a comprehensive view of management expectations regarding various ongoing and event-driven business-related aspects of the business (Loughran and McDonald, 2013).
[5] Cost elasticity is measured as the percentage change in costs for a percentage change in sales (see, for example, Holzhacker et al., 2015a, 2015b).

levels. Additionally, these findings validate our measures and support the importance of examining the tension between types of uncertainty and cost behavior.

We continue the analysis by examining the effect of uncertainty on asymmetric cost behavior. Prior research has found that costs increase, on average, more when current sales rise than they decrease when current sales fall by an equivalent amount. That is, cost elasticity is higher when sales in the current period rise than when they fall. The literature has termed this cost behavior *cost stickiness*. ABJ conjectured that firms experience these sticky costs because managers increase resources when sales rise but make a deliberate decision to maintain unused resources when they expect a current drop in sales to be temporary. They do so in response to uncertainty about future demand, to minimize both current and future adjustment costs (e.g., severance payments or disposal costs of existing equipment and training costs or installation costs of new equipment when demand bounces back) until the uncertainty is resolved. Consistent with the conjecture in ABJ, we find that managerial perception of the *overall* uncertainty increases the degree of cost asymmetry. While the individual effect of demand uncertainty on the degree of cost asymmetry is in the predicted direction, it is statistically insignificant.

Finally, we analyze the interaction between managers' uncertainty-driven resource allocation decisions and the amount of unused resources available at the beginning of the current period. Specifically, we examine whether the amount of unused resources affects the association between uncertainty and the degree of cost asymmetry. Consistent with our prediction, we find that when the amount of unused resources available at the beginning of the current period is *high*, uncertainty has no impact on the degree of cost asymmetry. This finding suggests that the motivation to delay a reduction in resources in the face of high uncertainty when current sales fall is attenuated because the combination of the existing and newly created unused resources may exceed acceptability threshold. Additionally, managers' motivation to increase resources when current sales rise when facing uncertainty is washed away because a high amount of unused resources enables them to delay an increase in resources until the uncertainty is resolved. In contrast, we find that when there are *fewer* unused resources, the degree of cost asymmetry increases with uncertainty. This finding suggests that the ability of managers to delay an increase in resources until the uncertainty is resolved is restricted by the low amount of unused resources and that the low amount of unused resources intensifies their motivation to delay a costly reduction in resources in the face of high uncertainty.

This study contributes to the extant literature in the following ways. First, our study promotes the understanding of the role of managerial perception of uncertainty and its components in shaping a firm's cost behavior. We do so by constructing a large-sample, firm-specific, time-varying, and forward-looking empirical measures of managers' perceptions of the overall, price, and demand uncertainty and by documenting the distinct, incremental, and opposing effects of these measures on a firm's cost behavior. Accordingly, our empirical evidence provides validation of the key theoretical arguments in the literature that uncertainty and its components motivate managers to make contextual resource allocation decisions that impact cost elasticity and underscores the importance of distinguishing and controlling for the tension between different types of uncertainties.

Second, our findings of differential effects of uncertainty on cost elasticity depending on both the sign of the change in current sales and on the level of unused resources available at the beginning of the current period validate the theoretical argument on the relation between uncertainty and asymmetric cost behavior and suggest that the impact of uncertainty on a firm's cost behavior and on managers' operating decisions depends on other economic drivers. Moreover, research on the relation between uncertainty and cost asymmetry needs to consider the impact of unused resources on this relation, as uncertainty is not associated with cost asymmetry for high amounts of unused resources.

Finally, we heed the call of Banker and Byzalov (2014) for research that integrates financial and managerial issues (e.g., Chen et al., 2012; Kama and Weiss, 2013; Banker et al., 2016; Chen et al., 2019) by incorporating in our analysis of managerial resource adjustment decisions measures of textual analysis borrowed from financial accounting research.

We develop our hypotheses in Section 2. Section 3 describes the sample and our definitions of the empirical variables. Our empirical findings are detailed in Section 4. Section 5 provides the conclusions of this study.

2. Background and hypotheses development

2.1 The effect of uncertainty on cost elasticity

The extant theoretical research studies the idiosyncratic impact of various types of uncertainty on a firm's cost behavior and on managers' operating decisions. One strand of this literature relies on a real-option theory that provides a decision model involving cost commitments made under price uncertainty. In their seminal paper, McDonald and Siegel (1985) consider a model of a price-taking firm who faces uncertain output price and has the option to temporarily and costlessly shut down production when the variable cost of production exceeds sales revenues. They demonstrate that the real option effect associated with price uncertainty is more valuable in production technologies characterized by a higher ratio of variable to fixed costs (i.e., a higher ratio of lower to higher adjustment costs). One implication of their model is that managers are likely to shift to a *more* elastic cost function (e.g., low adjustment costs, a high proportion of variable to fixed costs) in the face of high price uncertainty (e.g., Kallapur and Eldenburg, 2005). A more elastic cost function provides managers with the flexibility to respond to changes in economic conditions, which becomes more valuable as price uncertainty increases.[6]

Another strand of this literature examines the relation between demand uncertainty and cost elasticity. Specifically, Banker et al. (2014b) derive an analytical model that focuses on the relation between demand (or volume) uncertainty and cost elasticity. In their model, high demand uncertainty can lead to either high or low demand realizations. Due to the embedded convexity of the cost function in volume, high demand realizations could lead to disproportionately large congestion costs (due to reduced production capacity) which would dominate the cost associated with low demand realizations. Accordingly, they argue, firms facing demand uncertainty will increase their capacity of fixed resources which will result in a *negative* relation between demand uncertainty and cost elasticity.

Motivated by the theoretical literature, we begin our analysis by examining the association between the managerial perception of price and demand uncertainty and cost elasticity. We predict that:

H1a: Cost elasticity is increasing in the managerial perception of price uncertainty

H1b: Cost elasticity is decreasing in the managerial perception of demand uncertainty

[6] Management accounting textbooks argue that the amount of sales needed to break even increases as cost elasticity decreases (Horngren et al., 2012). This, in turn, implies that a lower degree of cost elasticity exposes the firm to a higher level of risk of losses and debt default, as well as higher volatility of earnings, which decreases the probability of meeting earnings targets. To reduce this risk, managers prefer a more elastic cost function in the face of high uncertainty.

Four prior studies examine empirically the effect of uncertainty on cost elasticity. Kallapur and Eldenburg (2005) build on the real options theory in McDonald and Siegel (1985) and find that uncertainty introduced by a change in Medicare reimbursement policy from cost-based reimbursement to flat fee results in managers choosing technologies with a higher ratio of variable to fixed costs for a sample of Washington state hospitals. Similarly, Holzhacker et al. (2015b) measure cost elasticity as the percentage change in cost for a percentage change in sales, and document that the higher uncertainty associated with a change in reimbursement regulation from full cost to fixed-fee increases cost elasticity in for-profit German hospitals (but not in nonprofit or government German hospitals). Holzhacker et al. (2015a) examine the association between cost elasticity and measures of demand and financial uncertainty for a sample of California hospitals. Their evidence suggests that demand and financial uncertainty motivate hospitals to shift to resource procurement with lower adjustment costs (measured as outsourcing, leases, and contracted labor hours). Finally, Banker et al. (2014b) provide an analytical model and document empirically a negative relation between demand uncertainty (measured as sales' variability using all the observations available for any given firm in the sample) and cost elasticity for manufacturing firms.[7]

2.2 The impact of uncertainty on asymmetric cost behavior

Prior literature has documented that costs increase, on average, more when current sales rise than they decrease when current sales fall by an equivalent amount and termed this cost behavior *sticky costs* (see ABJ, Banker and Chen, 2006; Kama and Weiss, 2013; Cannon, 2014,

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[7] Holzhacker et al. (2015a) measure *demand* uncertainty as the firm-level, time-series standard deviation of log change in a hospital's patient days using all the observations available for any given hospital in the sample. They suggest their results differ from Banker et al. (2014b) due to ownership differences between manufacturing firms and hospitals, resulting in different forms of compensations and economic incentives (e.g., performance-based versus equity-based incentives), and distinctive risk preferences.

Chen, Kama, and Lehavy, 2019, among others). This finding indicates that cost elasticity (measured as the percentage change in cost for a percentage change in sales) is higher when sales in the current period rise than when they fall. ABJ conjectured that firms experience these sticky costs because managers increase resources when sales rise but make a deliberate decision to maintain unused resources when they expect a current drop in sales to be temporary. They do so in response to uncertainty about future demand, to minimize both current and future adjustment costs (e.g., severance payments or disposal costs of existing equipment and training costs or installation costs of new equipment when demand bounces back) until the uncertainty is resolved.[8]

Following the argument in ABJ, we predict that managerial expectations of higher future uncertainty will exacerbate the degree of cost stickiness. Our second hypothesis is thus:

H2: Cost stickiness is increasing in the managerial perception of uncertainty

Empirically, the only two studies that have examined the association between measures of uncertainty and asymmetric cost behavior provide different findings. Holzhacker et al. (2015b) document that a one-time change in reimbursement regulation from full cost to fixed-fee *decreases* the degree of cost asymmetry in a sample of for-profit German hospitals, but has no effect on the cost asymmetry of nonprofit and government German hospitals. Lee et al. (2016) document that the asymmetry in cost behavior is stronger during election years than in non-election years.

[8] Inspired by these findings, several studies have documented more generalized forms of the asymmetric cost behavior (e.g., *anti-sticky* costs; Weiss, 2010) and its existence in a variety of different contexts. These studies generally concur with the argument that the deliberate managerial decisions to adjust resources in response to both sales increases and decreases is the primary driver of asymmetric cost behavior. See Banker and Byzalov (2014) for a review of this literature.

2.3 Does the impact of uncertainty on cost asymmetry depend on the amount of unused resources?

Another economic determinant of the sign and magnitude of cost asymmetry is the availability of unused resources at the beginning of the current period (e.g., Balakrishnan et al., 2004; Banker et al., 2014a; Chen et al., 2019). Prior studies have argued that the existence of *a greater* amount of unused resources at the beginning of the period reduces managers' need to increase existing resources in response to an increase in demand. However, when current demand decreases, the aggregated amount of unused resources carried over into the current period and the amount created during the current period may be sufficiently large to motivate managers to reduce these resources, resulting in an increase in cost elasticity. In all, managers who begin the period with a greater amount of unused resources will curtail resources at a higher rate when current sales fall than when they rise, resulting in a lower degree of cost stickiness (or even cost anti-stickiness).[9] By contrast, when managers face *fewer* unused resources they need to increase these resources when current demand rises, but may be able to retain some of the newly created unused resources when current sales decline. Consequently, when current sales rise and the amount of unused resources is low, managers will adjust resources more rapidly than when current sales decline; this behavior will intensify the extent of cost stickiness (Cannon, 2014).

While the literature indicates that the extent of cost asymmetry is affected by the amount of unused resources, whether unused resources affect the association between uncertainty and cost asymmetry remains an open question that has not been examined in prior studies. Accordingly, in

[9] Chen et al. (2019) examine the effect of a greater degree of unused resources on the sign of cost asymmetry and find that pessimistic managerial expectations result in anti-sticky cost behavior, while optimistic expectations reverse this relation, resulting in a sticky cost behavior. Their findings demonstrate that expectation-driven decisions can either attenuate or reverse the previously documented anti-sticky cost behavior associated with a greater amount of unused resources.

this section, we analyze whether the effect of uncertainty on the degree of cost asymmetry (i.e., H2) varies in the amount of unused resources carried over into the current period.

Consistent with our discussion above, we predict that the impact of uncertainty on cost stickiness will decline as the amount of unused resources increases. When the amount of unused resources carried over into the current period is *high*, the motivation to delay a reduction in resources *in the face of high uncertainty* when sales fall (compared to their motivation to increase resources when they rise) is attenuated because the combination of the existing and newly created unused resources may exceed acceptability threshold. Additionally, as the amount of unused resources increases, the motivation to increase resources when demand rises is attenuated because managers can rely on the existing amount of unused resources to respond to an increase in demand. This discussion leads to our third and final hypothesis:

H3: The positive association between uncertainty and the degree of cost stickiness is decreasing in the amount of unused resources carried over into the current period.

3. Sample, Variables, and Descriptive Statistics

3.1 Sample selection

We begin our analysis by obtaining a sample of all firms covered by Compustat from 1996 to 2017.[10] We then merge each firm-year observation in this sample with its 10-K and 10-K405 (hereafter 10-K) annual filings obtained from the SEC EDGAR online filings website.[11] We then exclude any firm-year observations associated with missing data, as well as any observations with

[10] We omit from the sample financial institutions (four-digit SIC codes 6000-6999) and public utilities (four-digit SIC 4900-4999). These firms and their corporate financial reporting are mandated by industry-specific regulations.
[11] Mandatory filing through the website was phased in by the SEC over a three-year period ending May 6, 1996.

non-positive values for sales revenue, SG&A expenses, number of employees or total assets or those with a ratio of SG&A expenses divided by sales that exceeds one. Finally, each year, we remove observations in the top and bottom 1% of the respective distribution. Our final sample comprises 45,870 firm-year observations. Monthly data from CRSP U.S. Treasury and Inflation is used to calculate the annual inflation rates for our sample period. We then use these estimates to adjust the dollar amounts of our variables for inflation. Our sample selection procedure is detailed in Table 1.

3.2 Empirical measure of the managerial perception of the overall uncertainty

We construct a measure of the managerial perception of the overall uncertainty based on the occurrence of uncertainty-related words in the management forward-looking statements (FLS) in the *Management Discussion and Analysis* section (MD&A) of 10-K reports.[12] FLS provide a managerial assessment of various ongoing and event-driven aspects of the business that may directly or indirectly impact future demand. According to Li (2010a), FLS refer to customer demand, competition, market conditions liquidity, pricing, income, production, and investments. Accordingly, the uncertainty embedded in these statements measures the uncertainty associated with these various aspects of the business, which ultimately determine future sales. We use this measure to conduct a comprehensive analysis of the cross-sectional variation in the relation between uncertainty and cost behavior.

Using a method similar to that described in Li (2010a, Appendix B), Bozanic et al. (2018, Appendix A), and Chen et al. (2019), we extract the MD&A section of each 10-K filing and

[12] Textual features of FLS have been shown to predict both current and future firm performance (e.g., Li, 2010a, 2010b; Wang and Hussainey, 2013).

identify the FLS in a given MD&A.[13] A sentence in an MD&A is marked as an FLS if it contains one or more words from the forward-looking dictionary and does not include words which indicate the sentence is legal boilerplate or refers to past events. These exclusion restrictions are needed to ensure that the sentence does not pertain to managers' prior expectations or is simply a boilerplate sentence. To construct the list of forward-looking words we use the dictionaries in Li (2010a) and Bozanic et al. (2018).[14] Next, we determine the percentage of uncertain FLS using the uncertainty words dictionary provided by Loughran and McDonald (2011).[15] We identify an FLS as uncertain if it contains one word or more from the dictionary of uncertain words. Prior studies have used this dictionary to examine the implications of uncertainty in various companies' filings, including the 10-K and S-1 (Loughran and McDonald, 2016). Specifically, research shows that 10-K filings with high levels of uncertain language have lower stock returns and higher abnormal trading volume around the 10-K filing and greater future return volatility (Loughran and McDonald 2011). Research also shows that greater uncertainty in the 10-K filing is positively associated with stricter loan contract terms (Ertugrul et al. 2017). Lastly, the level of uncertain text in the S-1 filing has been shown to be positively associated with IPO first-day returns, absolute offer price revisions, and future volatility (Loughran and McDonald 2013).

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[13] Chen et al. (2019) examine the effect of managerial expectations on cost asymmetry. Using the tone in the forward-looking statements of a sample of 10-K reports as a measure of managerial expectations, they document a positive and significant relation between the favorableness of FLS tone and the degree of cost stickiness and demonstrate that managers' expectation-driven decisions can reverse the previously documented anti-sticky cost behavior associated with a high degree of unused resources. Our paper differs from Chen et al. (2019) in that we focus on the effect of managerial perception of uncertainty (i.e., the second, rather than the first, moment) on *both* cost elasticity and cost asymmetry. The theoretical literature demonstrates the pivotal and distinct role of the second moment in determining a firm's cost elasticity. We control for the effect of FLS tone in our regression analysis.

[14] A large number of studies have documented the relation between FLS and future corporate events. For example, Muslu et al. (2015) find that the quantity of FLS is higher for firms with poor information environments, which investors find helpful in predicting future earnings; Bozanic et al. (2018) document a significant and positive relation between FLS in MD&A and both the accuracy of analyst earnings forecasts and investor reaction to corporate news.

[15] Numerous studies have used the dictionary-based word lists in Loughran and McDonald (2011). These lists are compiled from a large sample of 10-K filings and are therefore suitable for our paper. Loughran and McDonald (2016) argue that applying alternative dictionaries (e.g., Harvard's GI or Diction) that are not compiled from 10K filings (e.g., using management forecasts or conference calls) may result in spurious findings.

Since it is possible that the managerial perception of uncertainty for the current year affect their forward-looking statements in both the current and prior year's FLS, we compute the average uncertainty for firm *i* in year *t* as $Average\ FLS\_Uncertainty_{i,t}$ = ($FLS\_Uncertainty_{i,t-1}$ + $FLS\_Uncertainty_{i,t}$) / 2, where $FLS\_Uncertainty_{i,t}$ is the number of uncertain FLS sentences divided by the total number of sentences FLS for firm *i* in year *t*..[16] We then rank this variable into quintiles and transform the ranks of the uncertainty variable into a scaled-quintile variable whose values range from zero to one in increments of 0.25 (e.g., Rajgopal et al., 2003 and Amir et al., 2015). We denote this scaled-quintile measure of managerial perception $UC\_Total_{i,t}$.[17]

3.3 Empirical measure of the managerial perception of the price and demand uncertainty

Next, we decompose $FLS\_Uncertainty_{i,t}$ into the price, demand, and other uncertainty.[18] To do so, we decompose each uncertain FLS into price and demand based on self-created dictionaries of terms related to price and demand. The representative lists were constructed using the category name itself, terms used in reference to the category from prior research and our subjective judgment.[19] We then use the *i4Semantic* machine learning algorithm from Metaheuristica (http://www.metaheuristica.com/) to find the top 100 unique terms that are most similar to those in each representative list based upon how they are used in 10-K filings.[20] We

[16] Managers' perception of uncertainty is only observable to the researcher when the 10-K is released. However, we assume that these perceptions were formed during the year and thus determined managers' decisions throughout the year.
[17] Approximately 53% of the firm-year observations in our sample change their quintile ranking from year *t*-1 to year *t*, suggesting the measure varies over time.
[18] The "other" category are the terms not in the price or demand dictionaries.
[19] The representative list of words for price and demand are: (a) *price*: cost, expense, expenses, income, margin, performance results, price, prices, pricing, profit, reimbursement; (b) *demand*: competition, consumer demand, demand, market, market condition, market conditions, market position, new contract, revenues, sales.
[20] The i4Semantics machine learning algorithm is based on the idea that "You shall know a word by the company it keeps." (Firth 1957). One challenge to finding connections between words is that any given word occurs in many different contexts and the contexts in which the word appears affects its interpretation. In contrast to viewing a text as a "bag of words," the i4Semantics machine learning algorithm encodes each word into a vector space model, based

choose this machine learning approach over creating dictionaries based entirely on our judgment to mitigate subjectivity in the terms chosen for each category.

To calculate our empirical measures of price ($UC\_Price_{i,t}$), demand ($UC\_Demand_{i,t}$), and other ($UC\_Other_{i,t}$) uncertainty, we then follow these steps: first, for each sentence classified as uncertain FLS (i.e., each $FLS\_Uncertainty_{i,t}$), we separately compute the percentage of the number of price, demand, and other uncertainty words out of the total number of words in the given uncertain FLS sentence (these words are those 100 words contextually identified by the i4Semantic program; words not identified as either price or demand are "other"). Next, we calculate the sum of the percentage of words in the price, demand, and other terms in each uncertain FLS (from the first step) and divide each by the total number of FLS. The calculation is done this way so that the sum of *UC_Price*, *UC_Demand*, and *UC_Other* equals to our measure of the total FLS uncertainty. Similar to our empirical measure of *UC_Total*, we rank the average values of *UC_Price*, *UC_Demand*, and *UC_Other* into quintiles and transform these ranks into a scaled-quintile variable whose values range from zero to one in increments of 0.25.

3.4 Variable definitions

Our primary variables include the log change of Sales, General, and Administrative expenses (SGA) for firm *i* in year *t* (dependent variable defined as $\Delta lnSGA_{i,t}$); $\Delta lnSGA_{i,t}$ = log ($SGA_{i,t}$ / $SGA_{i,t-1}$), sales revenue (REV), the log change of sales revenue ($\Delta lnREV_{i,t}$ = log ($REV_{i,t}$ / $REV_{i,t-1}$)), and a dummy variable that takes the value of 1 if $REV_{i,t} < REV_{i,t-1}$ and 0 otherwise ($REVDEC_{i,t}$).

on the other words surrounding the given word (i.e., its "context"). The algorithm is implemented as a recurrent neural network and the algorithm is trying to solve a simple prediction problem of predicting the surrounding words in which the given word occurs. The resulting serialization of the recurrent neural network captures the semantic representation of the words. Term similarity is then assessed as the cosine similarity of the vectors associated with a given word.

Our choice of SGA as the dependent variable is motivated by the extant literature and assumes that managerial resource allocation decisions that affect administrative, marketing and distribution are most likely to manifest themselves in SGA. Empirically, SGA is likely to manifest managerial uncertainty-driven decisions because it typically includes items that are associated with non-zero adjustment costs that are subject to managerial discretion (e.g., employee-related expenses, rent, utilities, and insurance). We measure the amount of unused resources at the beginning of the period as the change in prior period sales (e.g., Banker et al., 2014a). Specifically, we define the amount of unused resources as low (high) if $REV_{i,t}$ in year t-1 is higher (lower) than that in year t-2. Accordingly, when sales have increased (decreased) in the past, managers are likely to begin the period with relatively low (high) amounts of unused resources.[21] Finally, we control for the effect of macro-economic changes using the real change in gross domestic product (ΔGDP_t), adjustment costs using asset intensity ($ASINT_{i,t}$), employee intensity ($EMPINT_{i,t}$); $ASINT_{i,t} = log\ (Assets_{i,t} / REV_{i,t})$; $EMPINT_{i,t} = log\ (Number\ of\ Employess_{i,t} / REV_{i,t})$, and the tone of the FLS; ($FLS\_Tone_{i,t}$) is the number of positive minus the number of negative words divided by one plus the number of positive and negative words in the FLS.

3.5 Descriptive statistics

Table 2 provides descriptive statistics for our empirical variables. Consistent with the values of these variables reported in prior studies, we find that the average values of $REV_{i,t}$ and

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[21] Similar to Chen et al. (2019), as a robustness test, we constructed two additional measures of unused resources and re-estimated our primary regressions. The first alternative measure categorizes observations as having a high degree of unused resources when the ratio (REV_{t-1}/REV_{t-2}) is less than 1 *and* the ratio (SGA_{t-1}/SGA_{t-2}) is greater than or equal to the ratio (REV_{t-1}/REV_{t-2}), and a low degree of unused resources otherwise. The second alternative measure classifies sample observations as having a high degree of unused resources when REV_{t-1}/REV_{t-2} is less than 1 *and* $Number\ of\ Employees_{t-1} /\ Number\ of\ Employees_{t-2}$ is greater than or equal to the decrease in prior sales, and a low degree of unused resources otherwise. These measures attempt to identify circumstances in which a decrease in sales was not accompanied by a proportional decrease in capacity. Such firms are likely associated with a high degree of unused resources at the beginning of the period. The inferences from Table 8 remain similar using these alternative measures.

$SGA_{i,t}$ ($REV_{i,t}$ = \$2,478 million and $SGA_{i,t}$ = \$441 million) are larger than their median values ($REV_{i,t}$ = \$314 million; $SGA_{i,t}$ = \$66 million). Furthermore, the log change of $REV_{i,t}$ and $SGA_{i,t}$ (mean is equal to 0.05 and 0.06, respectively), the ratio between $SGA_{i,t}$ and $REV_{i,t}$ ($SGA/ REV_{i,t}$, mean = 0.28), and the sales decline frequency (34% relative to 37% found in Banker et al. 2014a) are similar to those documented in prior studies. Finally, our mean and median $UC\_Total_{i,t}$ of 0.49 suggest that about half of FLS denote some uncertainty.[22]

Table 3 provides Pearson (above the diagonal) and Spearman (below the diagonal) correlations between the main variables.

4. Empirical Results

4.1 The impact of price and demand uncertainty on the degree of cost elasticity

We begin our empirical analysis by testing the impact of the managerial perception of price and demand uncertainty on the degree of cost elasticity. Specifically, we estimate the following regression model for the overall uncertainty:[23]

$$\Delta\ln SGA_{i,t} = \beta_0 + \gamma_0 UC\_Total_{it} + \beta_1 \Delta\ln REV_{i,t} + \gamma_1 UC\_Total_{it} \Delta\ln REV_{i,t} + \nu_1 ASINT_{it} + \nu_2 EMPINT_{it} + \nu_3 \Delta GDP_t + \nu_4 \text{FLS\_Tone}_{it} + (\lambda_1 ASINT_{it} + \lambda_2\ EMPINT_{it} + \lambda_3\ \Delta GDP_t + \lambda_4 \text{FLS\_Tone}_{it})\ \Delta\ln REV_{i,t} + \mu_{it} \tag{1a}$$

And, the regression model including the components of the overall uncertainty (UC_TOTAL_{it}):

[22] We note that the mean and median uncertainty of non-FLS is 0.13 (untabulated), suggesting that statements about the past or present are less uncertain. This statistic provides further validation for our measure.

[23] Because our regressions include fixed effects and clustering, we use the Stata function reghdfe to run our regressions. This function allows us to run these types of models more quickly in Stata. Note that while all of the regressions include an intercept term the function does not (natively) report an intercept and therefore the intercept terms are unreported in the tables. Following Petersen (2009), observations in all our regression models are clustered by firm and year to provide standard errors that are robust to autocorrelation and heteroscedasticity.

$$\Delta\ln SGA_{i,t} = \beta_0 + \gamma_{0a} UC\_Price_{it} + \gamma_{0b} UC\_Demand_{it} + \gamma_{0c} UC\_Other_{it} + \beta_1 \Delta\ln REV_{i,t} + (\gamma_2 UC\_Price_{it} + \gamma_3 UC\_Demand_{it} + \gamma_4 UC\_Other_{it}) \Delta\ln REV_{i,t} + \nu_1 ASINT_{it} + \nu_2 EMPINT_{it} + \nu_3 \Delta GDP_t + \nu_4 \text{FLS\_Tone}_{it} + (\lambda_1 ASINT_{it} + \lambda_2\, EMPINT_{it} + \lambda_3\, \Delta GDP_t + \lambda_4 \text{FLS\_Tone}_{it})\, \Delta\ln REV_{i,t} + \mu_{it} \qquad (1b)$$

Column (1) of Table 4 reports the results from estimating the relation between the log change in SGA expenses and the log change in sales. Similar to previous studies, we document that the coefficient estimate on β_1 (0.565) is positive and significant. This result indicates that a one percent increase in sales is associated with a 56.5 basis points (bps) increase in SG&A expenses. In Column (2) we show the results of estimating regression equation (1a) including control variables for the level of asset intensity, employee intensity, the real change in GDP, and the tone of FLS (the first three control variables are similar to those in Holzhacker et al., 2015a, 2015b; we control for FLS tone based on the findings in Chen et al., 2019). The overall coefficient on *ΔlnREV* remains positive and significant at 0.570 $(= \beta_1 + \lambda_1 \overline{ASINT} + \lambda_2 \overline{EMPINT} + \lambda_3 \overline{\Delta GDP} + +\lambda_4 \overline{\Delta\text{FLS\_Tone}})$.

The results in Column (3) indicate that the coefficient on the interaction between the overall level of uncertainty (*UC_TOTAL)* and *ΔlnREV*, γ_1, is positive and significant. This result suggests that when managers expect the lowest level of uncertainty (*UC_TOTAL=0*), the degree of cost elasticity, β_1, is 0.542, positive and significant. Markedly, when management expects the highest level of uncertainty (*UC_TOTAL*=1), cost elasticity significantly increases by 0.044 to 0.586. In Column (4) we show the results of estimating regression equation (1a) including the control variables. The overall coefficient on *UC_TOTAL*ΔlnREV* remains positive and significant at 0.047.

The focus of the analysis in this section, however, is on the estimation of the individual and combined effects of each uncertainty component (*UC_Price, UC_Demand, UC_Other*) on cost elasticity. Column (6) of Table 4 presents the results of estimating regression equation (1b) that replaces the total uncertainty with price, demand, and other uncertainty and includes all the control variables. As can be seen in this column, the coefficient estimates on the interactions between *UC_Price, UC_Other*, and *ΔlnREV*, γ_2 and γ_4, are positive and significant (0.041 and 0.076, respectively) while the coefficient on the interaction between *UC_Demand* and *ΔlnREV*, γ_3, is negative and significant (-0.072). These findings uniformly support the predictions in H1a and H1b regarding the positive relation between cost elasticity and price uncertainty and the negative one between cost elasticity and demand uncertainty.

Next, we turn to the analysis of the tension between the individual effects of price and demand uncertainty on cost elasticity. Panel B of Table 4 reports the degree of elasticity for four different combinations of price and demand uncertainty. As can be seen, when both price and demand uncertainty are either extremely high or extremely low (i.e., when both are in quintile 1 or both are in quintile 5), the degree of cost elasticity is statistically the same (0.586 vs. 0.555, *p*-value of the difference is equal to 0.185). This finding suggests that when both the positive effect of price uncertainty and the negative effect of demand uncertainty on cost elasticity are the *strongest*, these two forces fully negate each other and the elasticity is statistically similar to the case in which both price and demand uncertainty are the weakest.

In contrast, when the positive effect of price uncertainty on elasticity is the strongest and the negative effect of demand uncertainty is the weakest (i.e., 0.627 associated with quintile 5 of price uncertainty and quintile 1 of demand uncertainty), the degree of elasticity is significantly greater relative to a case when the negative effect of demand uncertainty is the strongest and the positive effect of price uncertainty on elasticity in the weakest (i.e., 0.514 associated with quintile 1 of price uncertainty and quintiles 5 of demand uncertainty). These findings further support the hypothesized tension between the positive effect of price uncertainty vs. the negative effect of demand uncertainty on cost elasticity.

An additional test aimed at understanding the tension between the uncertainty components, we estimate regression equation (1b) within quintiles of uncertainty components. As can be seen in Panel A of Table 5, there is a little variation in the effect of price uncertainty estimated within quintiles of demand uncertainty. In contrast, when estimating the effect of demand uncertainty within quintiles of price uncertainty (Panel B), we find that the negative relation between demand uncertainty and elasticity primarily holds when price uncertainty is moderate to low (quintiles 1-3) but is insignificant when the managerial perception of price uncertainty is higher. This finding suggests that managerial concern regarding the cost of resource congestion associated with demand uncertainty is heightened when price uncertainty is low but is attenuated when their concern regarding profit margin associated with price uncertainty is high. Finally, there are no discernible patterns in the coefficient estimates on price and demand uncertainty within quintiles of *UC_Other* reported in Panel C.

Finally, following the evidence in Chen et al. (2019) regarding the effects of the tone of managerial expectations on a firm cost behavior, we examine whether the tone of managerial expectation moderates the relation between managerial expectations of uncertainty and its components and cost elasticity. Table 6 presents the results of estimating the impact of uncertainty on cost elasticity within quintiles of FLS tone. As can be seen, γ_1 and γ_4 (the coefficient estimates on the relation between total and other uncertainty and cost elasticity) are positive and mostly significant only when managerial expectations are pessimistic. This finding suggests that managerial incentive to shift to a more elastic cost structure is most pronounced when their perception of the overall (or other) uncertainty is accompanied by pessimism regarding future business success. The positive coefficient on γ_2 (the relation between price uncertainty and cost elasticity) is positive and significant only when managerial expectations are the most optimistic. Finally, consistent with the argument in Banker et al. (2014b), we find that γ_3 (the relation between demand uncertainty and cost elasticity) is negative and significant when managerial expectations are either the most optimistic (when they are most concerned about resource congestion costs) or the most pessimistic (when they are least concerned about resource congestion costs).

Taken together, the totality of the findings presented in this section support hypotheses H1a and H1b. First, the evidence that the degree of cost elasticity increases in the managerial perception of the overall and price uncertainty but is decreasing in their perception of demand uncertainty is consistent with the theory and underscores the importance of decomposing the overall uncertainty into price and demand to fully understand the relation between uncertainty and cost behavior. Second, the evidence presented in Panel B of table 4 and Table 5 regarding the tension between the respective roles of price and demand uncertainty validates our measures and provide further support for the individual and relative effect of each component of uncertainty and underscores the need to examine these effects jointly.[24]

[24]We note that empirically the elasticity measure might be affected by changes in cost structure (e.g., the ratio of variable to fixed costs) or by a deliberate change in costs (i.e., resources) for a given change in sales. Moreover, the effects of managerial perception of uncertainty on cost structure choices may be either ex-ante (e.g., changes to production technology) or ex-post (e.g., retaining unused resources). Like the extant literature, we do not empirically distinguish between these choices.

4.2 The impact of uncertainty on the degree of cost asymmetry

Next, we examine the impact of the managerial perception of uncertainty on the sign and magnitude of cost asymmetry (H2) by estimating the following regression model for the overall uncertainty:

$$\Delta\ln SGA_{it} = \beta_0 + \gamma_0 UC\_Total_{it} + (\beta_1 + \gamma_1 UC\_Total_{it})\Delta\ln REV_{it} + (\beta_2 + \gamma_2 UC\_Total_{it})\mathrm{REVDEC_{it}}\ \Delta lnREV_{it} + \ v_1 ASINT_{it} + \upsilon_2\mathrm{EMPINT_{it}} + \nu_3\Delta\mathrm{GDP}_t + \nu_4\mathrm{FLS\_Tone}_{it} + (\delta_1\mathrm{ASINT}_{it} + \ \delta_2\mathrm{EMPINT}_{it} + \ \delta_3\Delta GDP_t + \ \delta_4\mathrm{FLS\_Tone}_{it})\Delta\ln REV_{it} \ + (\delta_5\mathrm{ASINT}_{it} + \delta_6\mathrm{EMPINT}_{it} + \ \delta_7\Delta GDP_t + \ \delta_8\mathrm{FLS\_Tone}_{it})\mathrm{REVDEC}_{it}\Delta\ln REV_{it} \ + \varepsilon_{it} \qquad (2a)$$

As well as the regression model including the components of the overall uncertainty:

$$\Delta\ln SGA_{it} = \beta_0 + \gamma_{0a} UC\_Price_{it} + \gamma_{0b} UC\_Demand_{it} + \gamma_{0c} UC\_Other_{it} + (\beta_1 + \gamma_{1a} UC\_Price_{it} + \gamma_{1b} UC\_Demand_{it} + \gamma_{1c} UC\_Other_{it})\Delta\ln REV_{it} + (\beta_2 + \gamma_{2a} UC\_Price_{it} + \gamma_{2b} UC\_Demand_{it} + \gamma_{2c} UC\_Other_{it})\mathrm{REVDEC_{it}}\ \Delta lnREV_{it} + \ v_1 ASINT_{it} + \upsilon_2\mathrm{EMPINT_{it}} + \nu_3\Delta\mathrm{GDP}_t + \nu_4\mathrm{FLS\_Tone}_{it} + (\delta_1\mathrm{ASINT}_{it} + \ \delta_2\mathrm{EMPINT}_{it} + \ \delta_3\Delta GDP_t + \delta_4\mathrm{FLS\_Tone}_{it})\Delta\ln REV_{it} \ + (\delta_5\mathrm{ASINT}_{it} + \ \delta_6\mathrm{EMPINT}_{it} \ + \ \delta_7\Delta GDP_t + \delta_8\mathrm{FLS\_Tone}_{it})\mathrm{REVDEC}_{it}\Delta\ln REV_{it} \ + \varepsilon_{it} \qquad (2b)$$

As can be seen in Column (1) of Table 7, the coefficient estimates on β_1 and β_2 are 0.668 and -0.257, respectively, and are statistically significant. These results are consistent with those reported in prior studies and indicate that SG&A expenses increase by 0.668 percent in response to a one percent *increase* in current sales, but decrease by (66.8-25.7=) 41.1 bps in response to a one percent *decrease* in current sales. The coefficient estimate on β_2 signifies the degree of cost asymmetry. In Column (2) we report the findings of estimating regression equation (2a) including control variables for the level of asset intensity, employee intensity, the real change in GDP, and the FLS tone. The overall coefficient on *REVDEC*ΔlnREV* (the degree of asymmetry) remains negative and significant at -0.226 (reported at the bottom of the table).

As shown in Column (3), the coefficient estimate on the interaction between UC_Total_{it} and *REVDEC*ΔlnREV* (γ_2) is negative and significant (-0.102). Accordingly, when management expects the lowest degree of total uncertainty (UC_Total_{it} =0), the cost asymmetry coefficient, β_2, is -0.204, negative and significant, indicating cost stickiness. When management expects the highest level of uncertainty (the highest quintile of UC_Total_{it}), cost stickiness increases significantly by 0.102 to -0.306. This evidence supports our second hypothesis that the degree of cost stickiness is increasing in the managerial perception of uncertainty. In Column (4) we show the results of estimating regression equation (2a) including the control variables. The coefficient estimate on the interaction term *UC_Total*REVDEC*ΔlnREV* remains negative and significant at -0.068.

Columns 5 and 6 of Table 7 report the results of estimating regression (2b) of the effect of each uncertainty component (*UC_Price, UC_Demand, UC_Other*) on the cost asymmetry. As can be seen, the coefficient estimates remain negative but are largely insignificant (in contrast to the evidence in columns 3 and 4 regarding the significant effect of the overall uncertainty on cost asymmetry). We note, however, that extant theory does not predict a specific relation between certain uncertainty components and the degree of cost asymmetry.

Combined, the evidence presented in Table 7 indicates overall uncertainty increases the degree of cost asymmetry. This evidence validates some of the theoretical arguments in the literature that the managerial perception of uncertainty plays an important role in shaping cost asymmetry, and empirically demonstrates the importance of analyzing cost behavior in the context of the managerial perception of uncertainty. While the theoretical argument in ABJ focuses on the role of demand uncertainty, empirically, we document a negative but statistically insignificant relation between our measure of demand uncertainty and cost asymmetry (perhaps due to lack of power).

4.3 Uncertainty, cost asymmetry, and the amount of unused resources

The results of estimating regression model (2a) separately for sub-samples of firm-years associated with a high and low amount of unused resources are reported in Table 8. Consistent with H3, we find that the impact of the managerial perception of uncertainty on the degree of cost asymmetry (γ_2) is significant only when the initial amount of unused resources is low, but is statistically insignificant when this amount is high (-0.083 and 0.012). As reported at the bottom of Table 8, the difference between these two coefficients, 0.071, is not statistically significant. These findings inform the literature analyzing the association between uncertainty and cost elasticity that such analysis needs to consider both the sign of the change in sales and the amount of available unused resources when drawing inferences about this association.

4.4 Additional analyses

We conduct the following analyses (untabulated for brevity) to test for the robustness of our results. First, we re-run our regressions using (i) FLS uncertainty as a continuous variable, and (ii) the change in the continuous variable. Second, we re-run our analyses controlling for change in inventory, as prior studies suggest that this variable may affect cost elasticity (e.g., Banker et al., 2014b). Third, as reported in footnote 20, our results remain similar after employing two alternative measures of the amount of unused resources. Fourth, to examine whether changes in elasticity stem from changes in costs or changes in prices, we control for the change in the industry Producer Price Index (PPI) by the North American Industry Classification System (NAICS) using data from the U.S. Bureau of Labor Statistics. The qualitative results for all of the abovementioned robustness tests remain similar to those in our main analyses.

5. Conclusion

This study documents empirically the role of the managerial perception of uncertainty and its components in shaping a firm's cost behavior. Using the percentage of forward-looking-statements in 10-K reports containing uncertainty words as a measure of managerial perception of overall uncertainty, we find a positive and significant association between our measure and cost elasticity. This association remains positive and significant when sales in the current period *rise*, but turn insignificant when sales in the current period *fall*, jointly leading to a positive association between uncertainty and cost stickiness. Importantly, we find that the degree of cost elasticity increases in the managerial perception of the price uncertainty but is decreasing in their perception of demand uncertainty. This evidence is consistent with the theory and underscores the importance of decomposing the overall uncertainty into price and demand to fully understand the relation between uncertainty and cost behavior. We also find the amount of unused resources affects the association between total uncertainty and the degree of cost stickiness when the amount of unused resources carried over into the current period is *low* However, when the amount of unused resources is *high*, uncertainty does not affect elasticity when sales either rise or fall, resulting in an insignificant change in the degree of cost stickiness.

Taken together, this study advances our understanding of the determinants of firms' cost behavior and the role of these determinants in the context of other economic factors such as the change in demand and the degree of unused resources. Moreover, our study illustrates combining the textual properties of corporate financial disclosures to further our understanding of managerial resource allocation decisions. We hope that future work will exploit other features of financial reports to explore additional aspects traditionally deemed as pertaining to managerial accounting research.

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TABLE 1
Sample Selection

	Observations
(1) Initial sample: Firm-year observations available on Compustat, 1996 - 2017 excluding financial institutions and public utilities	231,236
(2) 10-K MD&A, SEC EDGAR online filing, 1996 - 2017	148,343
Number of observations after merging (1) and (2)	91,690
Excluding observations without required data	(45,820)
Full sample	**45,870**

Note: The initial sample includes all public firms covered by Compustat. We exclude financial institutions and public utilities (4-digit SIC codes 6000-6999 and 4900-4999). In the second step we include all 10-K filings covered by the SEC EDGAR online filings website and merge the data with the data obtained from Compustat in the first step. We then delete observations without valid data on the estimated variables, as well as firm-year observations with SG&A expenses-to-sales ratio greater than one, and the top and bottom 1% of the estimated variables in the regression models.

TABLE 2
Descriptive Statistics

Variable	Mean	Std. Dev.	25th Pctl	Median	75th Pctl
$REV_{i,t}$	2,477.74	11,486.08	83.77	314.18	1,263.94
$SGA_{i,t}$	441.25	1,994.89	20.86	66.10	231.62
$\Delta lnREV_{i,t}$	0.05	0.24	-0.05	0.04	0.16
$\Delta lnSGA_{i,t}$	0.06	0.21	-0.05	0.05	0.15
$SGA/REV_{i,t}$	0.28	0.20	0.13	0.24	0.39
$ASINT_{i,t}$	0.15	0.79	-0.36	0.04	0.52
$EMPINT_{i,t}$	-5.51	0.83	-5.94	-5.46	-5.03
$\Delta\ GDP_t$	2.59	1.74	1.90	2.60	4.40
$REVDEC_{i,t}$	0.34	0.47	0.00	0.00	1.00
$FLS\_Tone_{i,t}{}^{*}$	-0.19	0.21	-0.34	-0.21	-0.06
$UC\_Total_{i,t}{}^{*}$	0.49	0.10	0.43	0.49	0.55
$UC\_Price_{i,t}{}^{*}$	0.03	0.01	0.02	0.02	0.03
$UC\_Demand_{i,t}{}^{*}$	0.03	0.02	0.02	0.03	0.04
$UC\_Other_{i,t}{}^{*}$	0.43	0.08	0.38	0.43	0.48

Notes:
1. This table presents descriptive statistics for the main variables used in our analysis (N=45,870).
2. $Rev_{i,t}$ is the annual sales revenue of firm *i* in year *t* (in millions of dollars); $SGA_{i,t}$ is annual SG&A expenses (in millions of dollars); $\Delta lnREV_{i,t}$ is the log change of sales revenue [$\Delta lnREV_{i,t}$ = log ($REV_{i,t}$ / $REV_{i,t-1}$)]; $\Delta lnSGA_{i,t}$ is the log change of SGA [$\Delta lnSGA_{i,t}$ = log ($SGA_{i,t}$ / $SGA_{i,t-1}$)]; $SGA/REV_{i,t}$ is annual SG&A divided by annual sales revenue for firm i in year t; $ASINT_{i,t}$ is the log ratio of assets to $REV_{i,t}$ [$ASINT_{i,t}$ = log ($Assets_{i,t}$ / $REV_{i,t}$)]; $EMPINT_{i,t}$ is the log ratio of employees to $REV_{i,t}$ [$EMPINT_{i,t}$ = log ($Employees_{i,t}$ / $REV_{i,t}$)]; $\Delta GDP_{i,t}$ is the real annual percentage change in GDP; $REVDEC_{i,t}$ is an indicator variable that equals 1 if $REV_{i,t} < REV_{i,t-1}$ and 0 otherwise; $FLS\_Tone_{i,t}$ is the number of positive minus the number of negative words divided by one plus the number of positive and negative words in the FLS; $UC\_Total_{i,t}$ is the number of uncertain FLS sentences divided by the total number of FLS sentences for firm i in year t; $UC\_Price_{i,t}$, $UC\_Demand_{i,t}$, and $UC\_Other_{i,t}$ are the percent of price, demand, and other words in uncertain FLS.
3. *, the measure is reported non-standardized. All uncertainty variables are included in the regressions in quintiles ranging from 0 to 1.

Table 3

Pairwise Pearson and Spearman Correlations

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	$REV_{i,t}$		0.90	0.05	0.03	-0.40	-0.03	-0.25	-0.14	-0.08	0.05	-0.08	0.01	-0.15	-0.05
2	$SGA_{i,t}$	0.82		0.04	0.04	0.00	0.03	-0.22	-0.15	-0.08	0.02	-0.04	0.03	-0.08	-0.03
3	$\Delta lnREV_{i,t}$	-0.01	-0.01		0.66	-0.05	0.05	-0.04	0.15	-0.25	0.08	0.04	0.04	0.03	0.04
4	$\Delta lnSGA_{i,t}$	-0.02	-0.02	0.66		0.02	0.09	-0.01	0.13	-0.30	0.10	0.05	0.04	0.03	0.05
5	$SGA/REV_{i,t}$	-0.12	-0.01	-0.07	0.03		0.14	0.12	-0.02	0.01	-0.05	0.10	0.04	0.19	0.07
6	$ASINT_{i,t}$	-0.03	0.01	0.03	0.09	0.10		-0.09	-0.07	-0.04	-0.09	0.00	-0.05	-0.07	0.02
7	$EMPINT_{i,t}$	-0.15	-0.10	-0.04	-0.01	0.12	-0.08		0.21	0.03	0.05	0.00	-0.08	-0.05	0.01
8	ΔGDP_{t}	-0.04	-0.04	0.12	0.12	-0.03	-0.02	0.16		-0.01	0.15	-0.03	-0.02	-0.02	-0.04
9	$REVDEC_{i,t}$	0.00	-0.01	-0.21	-0.27	0.01	-0.04	0.03	0.00		-0.09	-0.03	-0.03	-0.01	-0.03
10	$FLS\_Tone_{i,t}$	0.02	0.04	0.08	0.10	-0.06	-0.10	0.05	0.14	-0.09		-0.16	-0.06	-0.06	-0.17
11	$UC\_Total_{i,t}$	-0.05	-0.04	0.03	0.05	0.10	0.01	0.01	-0.03	-0.03	-0.16		0.48	0.50	0.94
12	$UC\_Price_{i,t}$	-0.04	-0.05	0.03	0.04	0.07	-0.10	-0.08	-0.02	-0.03	-0.06	0.48		0.56	0.33
13	$UC\_Demand_{i,t}$	-0.08	-0.06	0.01	0.03	0.21	-0.11	-0.05	-0.02	-0.01	-0.06	0.50	0.56		0.34
14	$UC\_Other_{i,t}$	-0.04	-0.04	0.03	0.04	0.06	0.04	0.02	-0.04	-0.03	-0.17	0.94	0.33	0.34	

Note: This table presents pairwise Pearson (below diagonal) and Spearman correlation of our main variables. See Table 2 for variable definitions.

TABLE 4
The Impact of Uncertainty on Cost Elasticity

Panel A: Estimation of regressions (1a) and (1b)

Coefficient	Variable	(1)	(2)	(3)	(4)	(5)	(6)
γ_0	UC_Total_{it}			0.012***	0.015***		
				(3.45)	(4.46)		
γ_{0a}	UC_Price_{it}					0.010**	0.009**
						(2.42)	(2.15)
γ_{0b}	UC_Demand_{it}					0.010*	0.011**
						(2.05)	(2.50)
γ_{0c}	UC_Other_{it}					-0.000	0.004
						(-0.06)	(1.12)
β_1	$\Delta lnREV_{it}$	0.565***	0.766***	0.542***	0.738***	0.552***	0.741***
		(25.38)	(11.47)	(21.54)	(10.82)	(23.39)	(11.14)
γ_1	$UC\_Total_{it} * \Delta lnREV_{it}$			0.044**	0.047***		
				(2.76)	(2.95)		
γ_2	$UC\_Price_{it} * \Delta lnREV_{it}$					0.007	0.041*
						(0.26)	(1.98)
γ_3	$UC\_Demand_{it} * \Delta lnREV_{it}$					-0.059**	-0.072***
						(-2.16)	(-2.95)
γ_4	$UC\_Other_{it} * \Delta lnREV_{it}$					0.081***	0.076***
						(5.00)	(4.45)
Control Variables							
ν_1	$ASINT_{it}$		0.032***		0.032***		0.032***
			(9.91)		(9.88)		(9.89)
ν_2	$EMPINT_{it}$		0.002		0.002		0.003
			(1.07)		(1.07)		(1.19)
ν_3	ΔGDP_t		0.002		0.002		0.002
			(0.73)		(0.73)		(0.75)
ν_4	FLS_Tone_{it}		0.025***		0.027***		0.026***
			(5.62)		(6.54)		(6.29)
λ_1	$ASINT_{it} * \Delta lnREV_{it}$		-0.061***		-0.061***		-0.064***
			(-6.47)		(-6.48)		(-6.64)
λ_2	$EMPINT_{it} * \Delta lnREV_{it}$		0.048***		0.048***		0.047***
			(4.57)		(4.57)		(4.51)
λ_3	$\Delta GDP_t * \Delta lnREV_{it}$		0.020*		0.019*		0.019*
			(2.05)		(1.99)		(2.03)
λ_4	$FLS\_Tone_{it} * \Delta lnREV_{it}$		0.050*		0.055**		0.057**
			(1.97)		(2.25)		(2.32)
Overall Degree of Elasticity ($= \beta_1 + \lambda_1 \overline{ASINT} + \lambda_2 \overline{EMPINT} + \lambda_3 \overline{\Delta GDP} + +\lambda_4 \overline{\Delta \text{FLS\_Tone}}$)			0.570		0.545		0.549
Prob > F			0.000		0.000		0.000
Industry FE		Included	Included	Included	Included	Included	Included
Adj-R^2		0.443	0.463	0.444	0.464	0.445	0.465
N		45,870	45,870	45,870	45,870	45,870	45,870

Table 4 - *Continued*

Panel B: Elasticity calculations within quintiles of price and demand uncertainty

Quintiles Price	Quintiles Demand	Elasticity Calculation	Value	Value = 0 Prob > F	Diff.	Diff.=0 Prob > F
1	1	$\beta_1 + \gamma_3 UC\_Other_{it} * 0.5 + \lambda_1 \overline{ASINT} + \lambda_2 \overline{EMPINT} + \lambda_3 \overline{\Delta GDP} + \lambda_4 \overline{\text{FLS\_Tone}}$	0.586	0.000		
5	5	$\beta_1 + \gamma_1 UC\_Price_{it} + \gamma_2 UC\_Demand_{it} + \gamma_3 UC\_Other_{it} * 0.5 + \lambda_1 \overline{ASINT} + \lambda_2 \overline{EMPINT} + \lambda_3 \overline{\Delta GDP} + \lambda_4 \overline{\text{FLS\_Tone}}$	0.555	0.000	0.032	0.185
5	1	$\beta_1 + \gamma_1 UC\_Price_{it} + \gamma_3 UC\_Other_{it} * 0.5 + \lambda_1 \overline{ASINT} + \lambda_2 \overline{EMPINT} + \lambda_3 \overline{\Delta GDP} + \lambda_4 \overline{\text{FLS\_Tone}}$	0.627	0.000		
1	5	$\beta_1 + \gamma_2 UC\_Demand_{it} + \gamma_3 UC\_Other_{it} * 0.5 + \lambda_1 \overline{ASINT} + \lambda_2 \overline{EMPINT} + \lambda_3 \overline{\Delta GDP} + \lambda_4 \overline{\text{FLS\_Tone}}$	0.514	0.000	0.113	0.009

Notes:

1. Panel A presents the coefficients and the associated t-statistics (in parentheses) for the following regression model in columns 3-4:

$$\begin{aligned}\Delta\ln SGA_{i,t} = {} & \beta_0 + \gamma_0 UC\_Total_{it} + \beta_1 \Delta\ln REV_{i,t} + \gamma_1 UC\_Total_{it} \Delta\ln REV_{i,t} + \nu_1 ASINT_{it} \\ & + \nu_2 EMPINT_{it} + \nu_3 \Delta GDP_t + \nu_4 \text{FLS\_Tone}_{it} \\ & + (\lambda_1 ASINT_{it} + \lambda_2\, EMPINT_{it} + \lambda_3\, \Delta GDP_t + \lambda_4 \text{FLS\_Tone}_{it})\, \Delta\ln REV_{i,t} + \mu_{it}\end{aligned}$$

   And, the following regression model in columns 5-6:

$$\begin{aligned}\Delta\ln SGA_{i,t} = {} & \beta_0 + \gamma_{0a} UC\_Price_{it} + \gamma_{0b} UC\_Demand_{it} + \gamma_{0c} UC\_Other_{it} + \beta_1 \Delta\ln REV_{i,t} \\ & + (\gamma_1 UC\_Price_{it} + \gamma_2 UC\_Demand_{it} + \gamma_3 UC\_Other_{it}) \Delta\ln REV_{i,t} + \nu_1 ASINT_{it} \\ & + \nu_2 EMPINT_{it} + \nu_3 \Delta GDP_t + \nu_4 \text{FLS\_Tone}_{it} \\ & + (\lambda_1 ASINT_{it} + \lambda_2\, EMPINT_{it} + \lambda_3\, \Delta GDP_t + \lambda_4 \text{FLS\_Tone}_{it})\, \Delta\ln REV_{i,t} + \mu_{it}\end{aligned}$$

2. Panel B presents the overall elasticity calculations for combinations of the highest and lowest quintiles of price and demand uncertainty as well as statistical tests of differences between the categories.
3. See Table 2 for variable definitions.
4. *, **, *** - Significantly different from zero at the 0.10, 0.05, and 0.01 levels, respectively.

TABLE 5

The Impact of Uncertainty on Cost Elasticity, by Quintiles of Uncertainty Components

Panel A: Cost Elasticity Within Quintiles of Demand Uncertainty

		Quintiles of Demand Uncertainty				
		1	2	3	4	5
Coefficient	Variable	(1)	(2)	(3)	(4)	(5)
γ_{0a}	*UC_Price* $_{it}$	0.019**	0.012	0.004	0.009	-0.001
		(2.33)	(1.70)	(0.76)	(1.38)	(-0.06)
γ_{0c}	*UC_Other* $_{it}$	0.003	0.006	0.007	-0.002	0.004
		(0.51)	(1.04)	(1.48)	(-0.31)	(0.52)
β_1	*ΔlnREV* $_{it}$	0.591***	0.954***	0.747***	0.618***	0.648***
		(5.07)	(10.29)	(5.46)	(8.12)	(9.97)
γ_2	*UC_Price* $_{it}$ * *ΔlnREV* $_{it}$	-0.001	0.066	0.001	0.070	0.060
		(-0.04)	(1.57)	(0.04)	(1.52)	(1.26)
γ_4	*UC_Other* $_{it}$ * *ΔlnREV* $_{it}$	0.046	0.087***	0.130***	0.094**	0.017
		(1.07)	(4.27)	(5.15)	(2.28)	(0.62)
Control Variables		Included	Included	Included	Included	Included
Industry FE		Included	Included	Included	Included	Included
Adj-R^2		0.470	0.461	0.456	0.437	0.502
N		9,170	9,173	9,169	9,170	9,170

Panel B: Cost Elasticity Within Quintiles of Price Uncertainty

		Quintiles of Price Uncertainty				
		1	2	3	4	5
Coefficient	Variable	(1)	(2)	(3)	(4)	(5)
γ_{0b}	*UC_Demand* $_{it}$	0.010*	0.022***	0.015*	-0.003	0.012
		(1.73)	(4.16)	(1.84)	(-0.29)	(1.23)
γ_{0c}	*UC_Other* $_{it}$	0.001	0.011*	0.007	-0.002	0.000
		(0.13)	(1.97)	(1.22)	(-0.37)	(0.02)
β_1	*ΔlnREV* $_{it}$	0.652***	0.828***	1.010***	0.595***	0.710***
		(4.94)	(8.53)	(17.62)	(4.33)	(5.72)
γ_3	*UC_Demand* $_{it}$ * *ΔlnREV* $_{it}$	-0.117**	-0.090*	-0.119**	-0.038	-0.021
		(-2.31)	(-1.98)	(-2.76)	(-1.40)	(-0.30)
γ_4	*UC_Other* $_{it}$ * *ΔlnREV* $_{it}$	0.087***	0.070**	0.045	0.080***	0.088**
		(2.89)	(2.31)	(1.44)	(2.87)	(2.23)
Control Variables		Included	Included	Included	Included	Included
Industry FE		Included	Included	Included	Included	Included
Adj-R^2		0.459	0.430	0.475	0.474	0.490
N		9,170	9,168	9,170	9,172	9,173

TABLE 5 - ***Continuted***

Panel C: Cost Elasticity Within Quintiles of Other Uncertainty

		Quintiles of Other Uncertainty				
		1	2	3	4	5
Coefficient	Variable	(1)	(2)	(3)	(4)	(5)
γ_{0a}	*UC_Price* $_{it}$	0.006	0.021***	0.010	0.010	-0.005
		(0.84)	(2.88)	(1.30)	(1.50)	(-0.67)
γ_{0b}	*UC_Demand* $_{it}$	0.010*	0.013*	0.013	0.016**	0.005
		(1.77)	(2.06)	(1.66)	(2.45)	(0.80)
β_1	*ΔlnREV* $_{it}$	0.651***	0.754***	0.718***	0.866***	0.907***
		(5.29)	(6.46)	(10.48)	(9.16)	(10.94)
γ_2	*UC_Price* $_{it}$ * *ΔlnREV* $_{it}$	0.077**	-0.022	0.050	-0.013	0.117***
		(2.31)	(-0.57)	(1.29)	(-0.31)	(3.52)
γ_3	*UC_Demand* $_{it}$ * *ΔlnREV* $_{it}$	-0.099***	-0.044	-0.075	-0.047	-0.109**
		(-2.90)	(-1.33)	(-1.70)	(-0.88)	(-2.26)
Control Variables		Included	Included	Included	Included	Included
Industry FE		Included	Included	Included	Included	Included
Adj-R^2		0.417	0.439	0.478	0.487	0.507
N		9,171	9,172	9,170	9,171	9,171

Notes:

1. Panel A of this table presents the coefficients and the associated t-statistics (in parentheses) for the following regression model, estimated within quintiles of demand uncertainty:

$$\begin{aligned}\Delta\ln SGA_{i,t} &= \beta_0 + \gamma_{0a} UC\_Price_{it} + \gamma_{0c} UC\_Other_{it} + \beta_1 \Delta\ln REV_{i,t} + \gamma_1 UC\_Price_{it} \Delta\ln REV_{i,t} \\ &+ \gamma_3 UC\_Other_{it} \Delta\ln REV_{i,t} + \nu_1 ASINT_{it} + \nu_2 EMPINT_{it} + \nu_3 \Delta GDP_t + \nu_4 \text{FLS\_Tone}_t \\ &+ (\lambda_1 ASINT_{it} + \lambda_2\, EMPINT_{it} + \lambda_3\, \Delta GDP_t + \lambda_4 \text{FLS\_Tone}_t)\, \Delta\ln REV_{i,t} + \mu_{it}\end{aligned}$$

2. Panel B of this table presents the coefficients and the associated t-statistics (in parentheses) for the following model, estimated within quintiles of price uncertainty:

$$\begin{aligned}\Delta\ln SGA_{i,t} &= \beta_0 + \gamma_{0b} UC\_Demand_{it} + \gamma_{0c} UC\_Other_{it} + \beta_1 \Delta\ln REV_{i,t} + \gamma_2 UC\_Demand_{it} \Delta\ln REV_{i,t} \\ &+ \gamma_3 UC\_Other_{it} \Delta\ln REV_{i,t} + \nu_1 ASINT_{it} + \nu_2 EMPINT_{it} + \nu_3 \Delta GDP_t + \nu_4 \text{FLS\_Tone}_t \\ &+ (\lambda_1 ASINT_{it} + \lambda_2\, EMPINT_{it} + \lambda_3\, \Delta GDP_t + \lambda_4 \text{FLS\_Tone}_t)\, \Delta\ln REV_{i,t} + \mu_{it}\end{aligned}$$

3. Panel C of this table presents the coefficients and the associated t-statistics (in parentheses) for the following model, estimated within quintiles of other uncertainty:

$$\begin{aligned}\Delta\ln SGA_{i,t} &= \beta_0 + \gamma_{0a} UC\_Price_{it} + \gamma_{0b} UC\_Demand_{it} + \beta_1 \Delta\ln REV_{i,t} + \gamma_1 UC\_Price_{it} \Delta\ln REV_{i,t} \\ &+ \gamma_2 UC\_Demand_{it} \Delta\ln REV_{i,t} + \nu_1 ASINT_{it} + \nu_2 EMPINT_{it} + \nu_3 \Delta GDP_t + \nu_4 \text{FLS\_Tone}_t \\ &+ (\lambda_1 ASINT_{it} + \lambda_2\, EMPINT_{it} + \lambda_3\, \Delta GDP_t + \lambda_4 \text{FLS\_Tone}_t)\, \Delta\ln REV_{i,t} + \mu_{it}\end{aligned}$$

4. See Table 2 for variable definitions.
5. *, **, *** - Significantly different from zero at the 0.10, 0.05, and 0.01 levels, respectively.

TABLE 6

The Impact of Uncertainty on Cost Elasticity within Quintiles of tone FLS (FLS_Tone)

		Quintiles of FLS_Tone									
		Pessimistic		2		3		4		Optimistic	
Coefficient	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
γ_0	UC_Total_{it}	0.019***		0.013**		0.013**		0.018***		0.017**	
		(3.64)		(2.44)		(2.52)		(3.48)		(2.64)	
γ_{0a}	UC_Price_{it}		0.009		0.011*		0.003		0.015*		0.007
			(0.97)		(1.89)		(0.35)		(2.05)		(0.85)
γ_{0b}	UC_Demand_{it}		0.006		0.005		0.022**		0.007		0.014**
			(0.98)		(0.51)		(2.36)		(0.87)		(2.24)
γ_{0c}	UC_Other_{it}		0.009		0.005		-0.002		0.005		0.006
			(1.64)		(1.01)		(-0.33)		(0.79)		(1.06)
β_1	$\Delta lnREV_{it}$	0.704***	0.706***	0.745***	0.746***	0.929***	0.928***	0.744***	0.746***	0.726***	0.744***
		(8.48)	(8.72)	(5.68)	(5.61)	(11.04)	(10.40)	(8.38)	(8.44)	(7.38)	(7.30)
γ_1	$UC\_Total_{it} * \Delta lnREV_{it}$	0.102***		0.052		-0.004		0.041		0.018	
		(3.64)		(1.27)		(-0.13)		(1.16)		(0.76)	
γ_2	$UC\_Price_{it} * \Delta lnREV_{it}$		0.027		0.018		0.093		-0.009		0.059*
			(0.61)		(0.38)		(1.55)		(-0.21)		(1.90)
γ_3	$UC\_Demand_{it} * \Delta lnREV_{it}$		-0.091*		-0.059		-0.097		-0.041		-0.095**
			(-2.01)		(-1.38)		(-1.57)		(-1.09)		(-2.68)
γ_4	$UC\_Other_{it} * \Delta lnREV_{it}$		0.142***		0.090**		0.024		0.078*		0.039
			(4.62)		(2.18)		(0.64)		(1.85)		(1.62)
<u>Control Variables</u>											
ν_1	$ASINT_{it}$	0.031***	0.031***	0.032***	0.032***	0.034***	0.034***	0.036***	0.037***	0.030***	0.030***
		(6.92)	(6.74)	(7.29)	(7.13)	(8.01)	(8.30)	(7.02)	(7.13)	(5.29)	(5.40)
ν_2	$EMPINT_{it}$	0.005*	0.005*	0.004	0.005	0.001	0.002	0.001	0.002	-0.001	-0.001
		(1.94)	(1.96)	(1.12)	(1.24)	(0.58)	(0.69)	(0.31)	(0.39)	(-0.20)	(-0.19)
ν_3	ΔGDP_t	-0.001	-0.001	0.001	0.001	0.001	0.001	0.004	0.004	0.002	0.003
		(-0.34)	(-0.25)	(0.43)	(0.44)	(0.36)	(0.36)	(1.55)	(1.58)	(1.45)	(1.51)
λ_1	$ASINT_{it} * \Delta lnREV_{it}$	-0.072***	-0.073***	-0.049**	-0.050**	-0.048***	-0.053***	-0.075***	-0.077***	-0.051***	-0.054***
		(-5.35)	(-5.82)	(-2.65)	(-2.83)	(-3.08)	(-3.37)	(-4.42)	(-4.45)	(-2.88)	(-2.91)
λ_2	$EMPINT_{it} * \Delta lnREV_{it}$	0.039**	0.036**	0.046**	0.046**	0.070***	0.071***	0.041***	0.040**	0.051***	0.051***
		(2.77)	(2.64)	(2.28)	(2.13)	(5.53)	(5.45)	(2.85)	(2.76)	(3.55)	(3.52)
λ_3	$\Delta GDP_t * \Delta lnREV_{it}$	0.002	0.002	0.016**	0.016**	0.016*	0.015*	0.016	0.016	0.050***	0.050***
		(0.20)	(0.17)	(2.10)	(2.11)	(1.81)	(1.80)	(1.51)	(1.50)	(3.66)	(3.71)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Overall Degree of Elasticity ($= \beta_1 + \lambda_1 \overline{ASINT} + \lambda_2 \overline{EMPINT} + \lambda_3 \overline{\Delta GDP} + +\lambda_4 \overline{\Delta \text{FLS\_Tone}}$)	0.486	0.501	0.524	0.527	0.579	0.567	0.548	0.557	0.570	0.582
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Industry FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Adj-R^2	0.426	0.427	0.442	0.442	0.444	0.446	0.463	0.464	0.531	0.533
N	9,170	9,170	9,171	9,171	9,173	9,173	9,168	9,168	9,173	9,173

Notes:

1. The table presents the coefficients and the associated t-statistics (in parentheses) for the following regression model in columns 1, 3, 5, 7, 9:

$$\Delta\ln SGA_{i,t} = \beta_0 + \gamma_0 UC_{it} + \beta_1 \Delta\ln REV_{i,t} + \gamma_1 UC_{it}\Delta\ln REV_{i,t} + \nu_1 ASINT_{it} + \nu_2 EMPINT_{it} + \nu_3 \Delta GDP_t + (\lambda_1 ASINT_{it} + \lambda_2\, EMPINT_{it} + \lambda_3\, \Delta GDP_t)\,\Delta\ln REV_{i,t} + \mu_{it}$$

   And, the following regression model in columns 2, 4, 6, 8, 10:

$$\Delta\ln SGA_{i,t} = \beta_0 + \gamma_{0a} UC\_Price_{it} + \gamma_{0b} UC\_Demand_{it} + \gamma_{0c} UC\_Other_{it} + \beta_1 \Delta\ln REV_{i,t} + \gamma_1 UC\_Price_{it}\Delta\ln REV_{i,t} + \gamma_2 UC\_Demand_{it}\Delta\ln REV_{i,t} + \gamma_3 UC\_Other_{it}\Delta\ln REV_{i,t} + \nu_1 ASINT_{it} + \nu_2 EMPINT_{it} + \nu_3 \Delta GDP_t + (\lambda_1 ASINT_{it} + \lambda_2\, EMPINT_{it} + \lambda_3\, \Delta GDP_t)\,\Delta\ln REV_{i,t} + \mu_{it}$$

2. See Table 2 for variable definitions.
3. *, **, *** - Significantly different from zero at the 0.10, 0.05, and 0.01 levels, respectively.

TABLE 7
The Impact of Uncertainty on Cost Asymmetry

Coefficient	Variable	Description	(1)	(2)	(3)	(4)	(5)	(6)
Benchmark Model								
β_1	$\Delta lnREV_{it}$	Sales Increase	0.668***	1.069***	0.625***	1.032***	0.621***	1.027***
			(23.23)	(11.11)	(19.71)	(11.00)	(19.91)	(10.86)
β_2	$REVDEC_{it} * \Delta lnREV_{it}$	Cost Asymmetry	-0.257***	-0.559***	-0.204***	-0.524***	-0.176***	-0.506***
			(-6.84)	(-3.76)	(-5.52)	(-3.48)	(-4.35)	(-3.37)
The Impact of Uncertainty								
γ_1	$UC\_Total_{it} * \Delta lnREV_{it}$	Sales Increase			0.080***	0.062***		
					(4.74)	(3.46)		
γ_{1a}	$UC\_Price_{it} * \Delta lnREV_{it}$						0.038	0.055*
							(1.60)	(1.89)
γ_{1b}	$UC\_Demand_{it} * \Delta lnREV_{it}$						-0.027	-0.038
							(-0.83)	(-1.11)
γ_{1c}	$UC\_Other_{it} * \Delta lnREV_{it}$						0.076***	0.057***
							(4.11)	(2.84)
γ_2	$UC\_Total_{it} * REVDEC_{it} * \Delta lnREV_{it}$	Cost Asymmetry			-0.102***	-0.068*		
					(-3.36)	(-2.03)		
γ_{2a}	$UC\_Price_{it} * REVDEC_{it} * \Delta lnREV_{it}$						-0.099**	-0.061
							(-2.31)	(-1.15)
γ_{2b}	$UC\_Demand_{it} * REVDEC_{it} * \Delta lnREV_{it}$						-0.033	-0.046
							(-0.67)	(-0.82)
γ_{2c}	$UC\_Other_{it} * REVDEC_{it} * \Delta lnREV_{it}$						-0.014	0.005
							(-0.56)	(0.15)
Control Variables (interactions with $\Delta lnREV_{i,t}$)								
δ_1	$ASINT_{it} * \Delta lnREV_{it}$	Asset Intensity		-0.036**		-0.036**		-0.038**
				(-2.61)		(-2.62)		(-2.74)
δ_2	$EMPINT_{it} * \Delta lnREV_{it}$	Employee Intensity		0.087***		0.087***		0.087***
				(6.51)		(6.57)		(6.58)
δ_3	$\Delta GDP_t * \Delta lnREV_{it}$	Change in GDP		0.017		0.016		0.017
				(1.47)		(1.37)		(1.43)
δ_4	$FLS\_Tone_{it} * \Delta lnREV_{it}$	Tone		0.061*		0.068**		0.069**
				(1.82)		(2.12)		(2.09)
Control Variables (interactions with $REVDEC_{i,t} * \Delta lnREV_{i,t}$)								
δ_5	$ASINT_{it} * REVDEC_{it} * \Delta lnREV_{it}$	Asset Intensity		-0.073***		-0.072***		-0.071***
				(-3.60)		(-3.58)		(-3.52)
δ_6	$EMPINT_{it} * REVDEC_{it} * \Delta lnREV_{it}$	Employee Intensity		-0.082***		-0.082***		-0.083***
				(-3.18)		(-3.21)		(-3.26)
δ_7	$\Delta GDP_t * REVDEC_{it} * \Delta lnREV_{it}$	Change in GDP		-0.021		-0.020		-0.021
				(-1.28)		(-1.20)		(-1.26)
δ_8	$FLS\_Tone_{it} * REVDEC_{it} * \Delta lnREV_{it}$	Tone		-0.106***		-0.112***		-0.111***
				(-2.95)		(-3.08)		(-2.93)

		(1)	(2)	(3)	(4)	(5)	(6)
Main effects							
γ_0	*UC_Total* $_{it}$				0.009**		
					(2.69)		
γ_{0a}	*UC_Price* $_{it}$						0.004
							(0.93)
γ_{0b}	*UC_Demand* $_{it}$						0.004
							(0.98)
γ_{0c}	*UC_Other* $_{it}$						0.005
							(1.31)
ν_1	*ASINT* $_{it}$		0.021***		0.021***		0.022***
			(7.06)		(7.06)		(7.11)
ν_2	*EMPINT* $_{it}$		-0.006**		-0.006**		-0.006**
			(-2.34)		(-2.32)		(-2.20)
ν_3	*ΔGDP* $_t$		0.000		0.000		0.000
			(0.23)		(0.31)		(0.28)
ν_4	*FLS_Tone* $_{it}$		0.018***		0.020***		0.020***
			(3.77)		(4.15)		(3.97)
Overall Cost Asymmetry $(= \beta_2 + \delta_1 \overline{ASINT} + \delta_2 \overline{EMPINT} + \delta_3 \overline{\Delta GDP} + \delta_4 \overline{\text{FLS\_Tone}}$			-0.226		-0.190		-0.166
Prob > F			0.000		0.000		0.000
Overall Cost Asymmetry $(= \beta_2 + \gamma_2 + \delta_1 \overline{ASINT} + \delta_2 \overline{EMPINT} + \delta_3 \overline{\Delta GDP} + \delta_4 \overline{\text{FLS\_Tone}}$					-0.258		-0.268
Prob > F					0.000		0.000
Industry FE		Included	Included	Included	Included	Included	Included
Adj-R^2		0.454	0.474	0.455	0.475	0.455	0.475
N		45,870	45,870	45,870	45,870	45,870	45,870

Notes:

1. The table presents the coefficients and the associated t-statistics (in parentheses) for the following regression model in columns 1-4:

$$\begin{aligned}\Delta\ln SGA_{it} = {} & \beta_0 + \gamma_0 UC\_Total_{it} + (\beta_1 + \gamma_1 UC\_Total_{it})\Delta\ln REV_{it} \\ & + (\beta_2 + \gamma_2 UC_{it})\text{REVDEC}_{\text{it}}\,\Delta lnREV_{it} + \nu_1 ASINT_{it} + \nu_2 \text{EMPINT}_{\text{it}} + \nu_3 \Delta\text{GDP}_t \\ & + \nu_4 \text{FLS\_Tone}_{it} + (\delta_1 \text{ASINT}_{it} + \delta_2 \text{EMPINT}_{it} + \delta_3 \Delta GDP_t \\ & + \delta_4 \text{FLS}_{\text{Tone }it})\Delta\ln REV_{it} + (\delta_5 \text{ASINT}_{it} + \delta_6 \text{EMPINT}_{it} + \delta_7 \Delta GDP_t \\ & + \delta_8 \text{FLS}_{\text{Tone }it})\text{REVDEC}_{it}\Delta\ln REV_{it} + \varepsilon_{it}\end{aligned}$$

And, the following regression model in columns 5-6:

$$\begin{aligned}\Delta\ln SGA_{it} = {} & \beta_0 + \gamma_{0a} UC\_Price_{it} + \gamma_{0b} UC\_Demand_{it} + \gamma_{0c} UC\_Other_{it} \\ & + (\beta_1 + \gamma_{1a} UC\_Price_{it} + \gamma_{1b} UC\_Demand_{it} + \gamma_{1c} UC\_Other_{it})\Delta\ln REV_{it} \\ & + (\beta_2 + \gamma_{2a} UC\_Price_{it} + \gamma_{2b} UC\_Demand_{it} \\ & + \gamma_{2c} UC\_Other_{it})\text{REVDEC}_{\text{it}}\,\Delta lnREV_{it} + \nu_1 ASINT_{it} + \nu_2 \text{EMPINT}_{\text{it}} + \nu_3 \Delta\text{GDP}_t \\ & + \nu_4 \text{FLS\_Tone}_{it} + (\delta_1 \text{ASINT}_{it} + \delta_2 \text{EMPINT}_{it} + \delta_3 \Delta GDP_t \\ & + \delta_4 \text{FLS\_Tone}_{it})\Delta\ln REV_{it} + (\delta_5 \text{ASINT}_{it} + \delta_6 \text{EMPINT}_{it} + \delta_7 \Delta GDP_t \\ & + \delta_8 \text{FLS}_{\text{Tone }it})\text{REVDEC}_{it}\Delta\ln REV_{it} + \varepsilon_{it}\end{aligned}$$

2. See Table 2 for variable definitions.
3. *, **, *** - Significantly different from zero at the 0.10, 0.05, and 0.01 levels, respectively.

TABLE 8
The Impact of Uncertainty on Cost Asymetry in Subsamples of High and Low Unused Resources

Coefficient	Variable	Description	(1)	(2)
			Unused Resources	
			High	Low
Benchmark Model				
β_1	$\Delta lnREV_{it}$	Sales Increase	0.860***	1.091***
			(10.76)	(9.58)
β_2	$REVDEC_{it} * \Delta lnREV_{it}$	Cost Asymmetry	-0.233	-0.731***
			(-1.71)	(-4.24)
The Impact of Uncertainty				
γ_1	$UC\_Total_{it} * \Delta lnREV_{it}$	Sales Increase	0.058	0.030
			(1.50)	(1.38)
γ_2	$UC\_Total_{it} * REVDEC_{it} * \Delta lnREV_{it}$	Cost Asymmetry	-0.012	-0.083**
			(-0.26)	(-2.23)
Control Variables (interactions with ΔlnREVi,t)				
δ_1	$ASINT_{it} * \Delta lnREV_{it}$	Asset Intensity	-0.004	-0.055***
			(-0.13)	(-4.40)
δ_2	$EMPINT_{it} * \Delta lnREV_{it}$	Employee Intensity	0.081***	0.084***
			(6.06)	(5.44)
δ_3	$\Delta GDP_t * \Delta lnREV_{it}$	Change in GDP	-0.004	0.020*
			(-0.36)	(1.78)
δ_4	$FLS\_Tone_{it} * \Delta lnREV_{it}$	Tone	0.125***	0.011
			(2.98)	(0.33)
Control Variables (interactions with $REVDEC_{i,t} * \Delta lnREV_{i,t}$)				
δ_5	$ASINT_{it} * REVDEC_{it} * \Delta lnREV_{it}$	Asset Intensity	-0.126***	0.002
			(-3.38)	(0.07)
δ_6	$EMPINT_{it} * REVDEC_{it} * \Delta lnREV_{it}$	Employee Intensity	-0.057**	-0.092***
			(-2.43)	(-3.35)
δ_7	$\Delta GDP_t * REVDEC_{it} * \Delta lnREV_{it}$	Change in GDP	0.003	-0.030
			(0.19)	(-1.37)
δ_8	$FLS\_Tone_{it} * REVDEC_{it} * \Delta lnREV_{it}$	Tone	-0.156**	-0.019
			(-2.59)	(-0.41)
Main effects				
γ_0	UC_Total_{it}		0.005	0.010**
			(1.09)	(2.65)
ν_1	$ASINT_{it}$		0.019***	0.022***
			(4.93)	(7.01)
ν_2	$EMPINT_{it}$		-0.001	-0.006**
			(-0.40)	(-2.47)
ν_3	ΔGDP_t		0.000	0.001
			(0.25)	(0.66)
ν_4	FLS_Tone_{it}		0.017**	0.017***
			(2.60)	(3.21)
Test of H3: γ_2 (High Slack) - γ_2 (Low Slack) = -0.012 - (-0.083) = 0.071, p-value = 0.239				
Industry FE			Included	Included
Adj-R^2			0.372	0.500
N			15,557	30,308

Notes:

1. The table presents the coefficients and the associated t-statistics (in parentheses) for the following regression model, for sub-samples of high amount of initial unused resources (prior sales decrease) and a low amount of initial unused resources (prior sales increase).:

$$\begin{aligned}\Delta\ln SGA_{it} = {} & \beta_0 + \gamma_0 UC\_Total_{it} + (\beta_1 + \gamma_1 UC\_Total_{it})\Delta\ln REV_{it} \\ & + (\beta_2 + \gamma_2 UC_{it})\mathrm{REVDEC}_{\mathrm{it}}\, \Delta lnREV_{it} + \ v_1 ASINT_{it} + v_2 \mathrm{EMPINT}_{\mathrm{it}} + \nu_3 \Delta\mathrm{GDP}_t \\ & + \nu_4 \mathrm{FLS\_Tone}_{it} + (\delta_1 \mathrm{ASINT}_{it} + \ \delta_2 \mathrm{EMPINT}_{it} + \ \delta_3 \Delta GDP_t \\ & + \ \delta_4 \mathrm{FLS}_{\mathrm{Tone}\ it})\Delta\ln REV_{it} \ + (\delta_5 \mathrm{ASINT}_{it} + \ \delta_6 \mathrm{EMPINT}_{it} + \ \delta_7 \Delta GDP_t \\ & + \ \delta_8 \mathrm{FLS}_{\mathrm{Tone}\ it})\mathrm{REVDEC}_{it}\Delta\ln REV_{it} \ + \varepsilon_{it}\end{aligned}$$

2. See Table 2 for variable definitions.
3. *, **, *** - Significantly different from zero at the 0.10, 0.05, and 0.01 levels, respectively.