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The managerial perception of uncertainty and cost elasticity

Jason V. Chen [a], Itay Kama [b], Reuven Lehavy [b,*]

[a] University of Illinois, Chicago, IL, USA
[b] University of Michigan, Ann Arbor, MI, USA

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ABSTRACT

Theoretical research demonstrates the important role of uncertainty in shaping a firm's cost elasticity. We contribute to this literature by analyzing the inherent tension between the effects of uncertainty about unit contribution margin (CM) and sales volume on cost elasticity. We identify the occurrence of words implying uncertainty in managerial forward-looking statements and employ a novel methodology to construct distinct measures of the managerial perceptions of overall, unit CM, and volume uncertainty. We find a significantly positive (negative) association between the uncertainty about unit CM (volume) and cost elasticity. These associations vary predictably with firm and industry characteristics. Our empirical evidence supports the theoretical argument that managerial perceptions of uncertainty and its components differentially influence their resource allocation decisions and suggests that any analysis of the relation between uncertainty and a firm's cost elasticity should specify the type of uncertainty as well as the firm and industry characteristics.

1. Introduction

Theoretical research has examined the impact of uncertainty on a firm's cost elasticity (for example, McDonald and Siegel, 1985; Banker et al., 2014).[1] This research argues that managers shift to a more elastic cost function under high uncertainty about unit contribution margin (output price minus the variable cost per unit), but to a less elastic cost function under high uncertainty about sales volume. Managers may shift to a more elastic cost function by opting for more flexible contractual commitments with employees or suppliers or technologies with a greater ratio of variable to fixed costs. While the impact of uncertainty on cost elasticity has been examined at the theoretical level, empirical evidence is based on only a handful of studies.[2] These studies typically focus on a single type of uncertainty, a specific industry (primarily hospitals), or a specific event (e.g., a change in price regulations). As such, they are not able to examine the contextual tension between the effects of various types of uncertainty on cost elasticity.

Our study extends this literature by providing a large-scale empirical analysis of the joint, incremental, and contextual effects of managerial perceptions of unit contribution margin (CM) and volume uncertainty on cost elasticity. We examine these effects for the entire sample as well as investigate whether the tension between the effects of these two sources of

* Corresponding author.
E-mail addresses: jchen19@uic.edu (J.V. Chen), ikama@umich.edu (I. Kama), rlehavy@umich.edu (R. Lehavy).

[1] Cost elasticity refers to the percentage change in costs for a one-percent change in output and is related to the proportion of fixed and variable costs. For a given percentage change in output, a firm with a higher proportion of variable to fixed costs will experience a larger change in costs, implying a greater cost elasticity (see, for example, Holzhacker, Krishnan, and Mahlendorf, 2015a, 2015b).

[2] We discuss these studies in greater detail in Section 2 (Kallapur and Eldenburg, 2005; Banker et al., 2014; Holzhacker et al., 2015a, 2015b).

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uncertainty varies by firm or industry characteristics. The analysis and conclusions of this paper are important because they promote our understanding of the impact of uncertainty on managerial resource allocation decisions, which, in turn, determine earnings. We focus on the uncertainty associated with unit CM and volume because of their central roles in determining firm profitability (as discussed in the extant literature and economic theory). In our analysis, unit CM uncertainty refers to the uncertainty about the output price minus variable cost per unit, while volume uncertainty refers to the variability in the physical volume to be produced.[3]

We begin our empirical analysis by examining the effect of the managerial perception of unit CM and volume uncertainty on a firm's cost elasticity. Theoretical models predict that unit CM and volume uncertainties have opposite effects on cost elasticity. For example, McDonald and Siegel (1985) predict that when managers perceive greater unit CM uncertainty, they choose a more elastic cost function to ensure the flexibility needed to respond to changes in economic conditions. This flexibility becomes more valuable as uncertainty increases. Banker et al. (2014) provide a theoretical model indicating that volume uncertainty leads managers to reduce elasticity by committing more capacity resources to mitigate the potential for disproportionally high congestion costs in high volume realizations (relative to the adverse consequences of losses in low volume realizations).[4]

We jointly test these predictions by constructing firm-specific and time-varying empirical measures of the managerial perception of the overall, unit CM, and volume uncertainty. These distinct empirical measures are based on a novel methodology that separately identifies the occurrence of overall, unit CM, and volume uncertainty-related words in forward-looking statements (FLS) included in the *Management Discussion and Analysis* section (MD&A) of 10-K filings. To validate our text-based uncertainty measures, we analyze how they vary across industries and the degree of industry concentration, as well as how they correlate with both Banker et al.'s (2014) measures of demand uncertainty and the standard deviation of commodity prices (including gold, oil, and coal) as well as monthly automobile sales.

Consistent with our predictions, we document a significantly *positive* association between uncertainty about unit CM and cost elasticity and a significantly *negative* association between volume uncertainty and cost elasticity. In examining the tension between both types of uncertainty, we find that, for our entire sample, the positive effect of unit CM uncertainty on cost elasticity is stronger than the negative effect of volume uncertainty.

We conduct several cross-sectional tests to provide further support for our predictions and measures. One objective of these tests is to examine whether the negative relation between volume uncertainty and cost elasticity is diminished (or even turns positive) when congestion costs are low, or the adverse consequences of losses in low volume realizations are greater. Specifically, we examine the relation between volume uncertainty and cost elasticity for the subsamples of firms that report work-in-process inventory (WiP) as well as for firms with low financial risk. Because firms with WiP inventory are likely to be associated with a longer production cycles, their ability to respond to the quantity demanded in high volume realizations is limited relative to other firms. This attribute will likely intensify their concern about the potential congestion costs in high volume realizations, leading to a more negative association between volume uncertainty and cost elasticity relative to other firms. Firms with low financial risk are likely to be less concerned with the adverse consequences of losses in low volume realizations due to their financial strength. Accordingly, we predict that low financial risk or the existence of WiP inventory intensifies the managerial *differential* concern about the congestion costs in high volume realizations relative to the adverse consequences of losses in low volume realizations, resulting in a greater negative association between volume uncertainty and cost elasticity. Empirically, we find a significantly *negative* relation between volume uncertainty and cost elasticity for the subsamples of firms that report work-in-process inventory (WiP) as well as for firms with low financial risk; this relation turns insignificant for the subsamples of firms that do not report WiP inventory or firms with high financial risk. The effect of unit CM uncertainty on cost elasticity remains significant and positive for all subsamples. These findings are consistent with and further support the congestion cost mechanism outlined in Banker et al. (2014).

We also conduct a set of industry-level analyses that examine the effect of uncertainty on cost elasticity for subsamples based on the level of industry concentration. We predict that the effect of unit CM and volume uncertainty on cost elasticity is less pronounced for firms operating in concentrated versus competitive industries. Firms in highly concentrated industries are characterized by greater market power over price, costs, and volume, and are therefore not as concerned about the effects of unit CM and volume uncertainty on cost elasticity compared to firms operating in more competitive industries. Empirically, we find that managerial perceptions of both unit CM and volume uncertainty play a significant role in determining cost elasticity only for firms operating in *unconcentrated* industries but not for those in *highly concentrated* industries.

[3] This approach is similar to that of Kallapur and Eldenburg (2005) and Holzhacker et al. (2015b), who examine the change in uncertainty associated with the contribution margin per unit introduced by a change in the Medicare reimbursement policy that affects the association between reimbursement revenue and costs; and that in Banker et al. (2014) and Holzhacker et al. (2015a), who proxy for volume uncertainty using sales variability and the variability of hospitals' patient days, respectively. Whereas Banker et al. (2014) and Holzhacker et al. (2015a) use the terms "demand uncertainty" and "volume uncertainty" interchangeably, we use the term volume uncertainty in this study because we employ direct proxies for unit CM versus volume uncertainty. See our further discussion in Section 2.

[4] When volume realizations are unusually high, variable inputs would need to increase, while the capacity of fixed inputs remains limited in the short-term. This, in turn, would lead to congestion costs associated with a decrease in the marginal productivity of the variable inputs and an increase in their marginal cost. The adverse consequences of losses in low volume realizations include a higher potential for losses and a greater risk of financial default. See our further discussion in Section 2.

Finally, we employ our consistent measurement approach and empirical definitions of unit CM and volume uncertainty to examine the seemingly contradictory prior findings that the relation between volume uncertainty and cost elasticity is negative in the manufacturing sector (Banker et al., 2014) but positive in the healthcare sector (Holzhacker et al. 2015a). Examining firms in these respective subsamples, we find that the negative association between our measure of volume uncertainty and cost elasticity continues to hold for manufacturing firms, but that volume uncertainty is *positively* associated with cost elasticity in the healthcare sector. This finding supports the argument that hospitals typically maintain excess capacity to reduce the adverse consequences associated with potential congestion (e.g., turning away patients, increased mortality rate, and lower reputation) and is consistent with our prediction that the negative relation between volume uncertainty and cost elasticity may turn positive when the congestion costs are low. In our final set of findings, we document that, for manufacturing firms, the negative effect of volume uncertainty and the positive effect of unit CM uncertainty on cost elasticity fully and statistically offset each other. Since both unit CM and volume uncertainty are positively related to elasticity in the healthcare sector, cost elasticity *more than doubles* when both types of uncertainty are at their highest versus lowest levels. Combined, our findings underscore the importance of examining the tension between types of uncertainty when analyzing their impact on cost elasticity.

Our study contributes to the extant literature by providing insights into the role of managerial perceptions of overall uncertainty and its components in shaping a firm's cost elasticity. We do so by (i) constructing firm-specific, time-varying, and forward-looking empirical measures of respective managerial perceptions of unit CM, volume, and overall uncertainty and (ii) documenting the joint, incremental, and opposing effects of these internally consistent measures on cost elasticity across different industry affiliations and firm attributes. Our findings illustrate varying effects of managerial perceptions of uncertainty on cost elasticity that are based on the different interplays between sources of uncertainty across industries and alternative economic determinants. Our findings underscore the need to understand the dynamics of this relationship in determining the effect of uncertainty on cost elasticity. Our study also validates theoretical arguments that the overall uncertainty and its components motivate managers to make contextual resource allocation decisions that impact cost elasticity.

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

The extant literature studies the distinct effects of several sources of uncertainty on a firm's cost elasticity. One strand of this literature focuses on the effect of uncertainty about unit contribution margin on cost elasticity. For example, McDonald and Siegel (1985) consider a model of a firm facing a decision on whether to operate or shut down its production plant. In their model, a firm has an option to temporarily and costlessly shut down production when the unit contribution margin is negative (i.e., when the variable cost per unit exceeds output price) to avoid incurring additional losses associated with production. In essence, the opportunity to avoid incurring variable costs in a later period is a real (European) option.

One of the innovations in McDonald and Siegel (1985) is that they explicitly incorporate into their model the effect of uncertainty about both output price and variable cost per unit (i.e., the uncertainty about the unit CM) on managers' decisions. They argue that the option to temporarily and costlessly shut down production is valuable only when there is uncertainty about the output price or the variable cost per unit. In the absence of such uncertainty, a firm can decide *ex-ante* whether to operate the production plant. Consistent with the real-option theory, their model shows that the value of the option to avoid incurring variable costs by temporarily and costlessly shutting down production is increasing with the degree of uncertainty about the unit CM.

One of the main inferences from the model in McDonald and Siegel (1985) is that the positive impact of the uncertainty about unit CM on the value of the real option increases with the degree of cost elasticity. A more elastic cost structure would reduce the costs associated with exercising the option to temporarily shut down production (when the unit CM is negative) due to the lower proportion of the unavoidable fixed costs. Therefore, managers are likely to prefer a cost structure with a higher ratio of variable to fixed costs in the presence of greater uncertainty about the unit CM. As discussed in footnote 1, we refer to the ratio of fixed and variable costs as cost elasticity (i.e., how costs respond to changes in output) and expect cost elasticity to increase in the presence of uncertainty.

In an empirical study, Kallapur and Eldenburg (2005) examine whether managers shift to a more elastic cost structure when unit CM uncertainty increases. Using a sample of Washington state hospitals, they find that managers who faced greater uncertainty about contribution margin due to the change from a cost-based to a flat fee Medicare reimbursement scheme choose a more elastic cost structure. Similarly, Holzhacker et al. (2015b) document that the higher uncertainty associated with a similar change in reimbursement policy is associated with an increase in cost elasticity in for-profit German hospitals (but not in nonprofit or government hospitals).[5]

[5] The change in reimbursement policy in Kallapur and Eldenburg (2005) and Holzhacker et al. (2015b) creates uncertainty about the ability of the reimbursement to cover the variable cost per unit, which, in turn, increases the uncertainty about unit CM. Their findings are based on a specific event related to the change in reimbursement policy for hospitals. This event serves as an indirect measure of a change in uncertainty that is specific to hospitals.

Motivated by the theoretical model and prior empirical findings, we state our first hypothesis:

H1: *Cost elasticity is increasing in the managerial perception of uncertainty about unit contribution margin.*

Our study is also related to a stream in the literature that examines the relation between uncertainty about sales volume and cost elasticity. Within this stream, Banker et al. (2014) develop an analytical model that examines this relation. In their model, higher volume uncertainty increases the frequency of both unusually high and unusually low realizations of volume. When volume realizations are unusually high, variable inputs would need to increase to meet demand, while the capacity of fixed inputs would remain constant in the short term. This response would then lead to congestion costs associated with a decrease in the marginal productivity of the variable inputs and an increase in their marginal cost (i.e., the short-run cost function is convex in volume). Because of this convexity, the expected congestion costs increase with volume uncertainty. That is, the increase in congestion costs associated with high volume realizations would exceed the decrease in costs associated with low volume realizations.[6] In order to reduce these expected congestion costs, managers facing uncertainty about volume are likely to *increase* the amount of fixed inputs, resulting in a lower ratio of variable to fixed costs, or a less elastic cost structure. Accordingly, Banker et al. (2014) argue that firms facing volume uncertainty would increase their fixed resource capacity, resulting in a *negative* relation between volume uncertainty and cost elasticity. Consistent with the prediction of their theoretical model, they empirically document a negative relation between cost elasticity and volume uncertainty (measured as the time-series standard deviation of a log change in sales using all observations for a given firm; hereafter, sales variability) for a sample of manufacturing firms.

In a related study, Holzhacker et al. (2015a) examine the relation between volume and financial uncertainties and cost elasticity for a sample of nonprofit and private for-profit California hospitals. In their paper, volume uncertainty is measured as the time-series standard deviation of a log change in a hospitals' patient days using all the observations available for a given hospital; hereafter, hospitals' patient day variability. They document that volume and financial uncertainties motivate hospitals to shift to a greater proportion of procured versus in-house resources (such as leases and contracted labor hours). These resources are less costly to adjust (e.g., the costs of hiring and separations of contracted versus payroll labor), resulting in a more elastic cost function. Accordingly, they conclude that hospital managers in their sample will shift to a more elastic cost structure in the presence of higher volume and financial uncertainties.

The findings in Holzhacker et al. (2015a) differ from those documented in Banker et al. (2014). They explain these differences by arguing that hospitals are likely associated with lower congestion costs. This would be the case because hospitals typically maintain excess capacity to allow them to respond to unusually high volume realizations and reduce the adverse consequences associated with potential congestion (e.g., turning away patients, increased mortality rate, and lower reputation). Accordingly, the congestion costs associated with high volume realizations are likely lower than those associated with low volume realizations (e.g., higher potential for losses and a greater risk of financial default). In order to diminish the adverse consequences of losses in low volume realization, Holzhacker et al. (2015a) argue that hospitals facing volume uncertainty will shift to a more elastic cost structure, resulting in a positive relation between volume uncertainty and cost elasticity.[7,8]

The discussion above suggests that, in general, the association between volume uncertainty and cost elasticity is affected by the relative magnitude of the congestion costs in high volume realizations versus the adverse consequences of losses in low volume realizations. When the congestion costs in high volume realizations dominate the adverse consequences of losses in low volume realizations, the relation between volume uncertainty and cost elasticity is expected to be negative. Based on the theoretical model and the empirical findings from prior studies, we expect this relation to hold for the full sample as well as a subsample of manufacturing firms. The negative relation between volume uncertainty and cost elasticity is expected to diminish (and even turn positive) when the congestion costs in high volume realizations decline or the adverse consequences of losses in low volume realizations intensify. We use our internally consistent set of empirical measures of volume uncertainty to examine the sign and magnitude of the association between volume uncertainty and cost elasticity for the full sample and across various sub-samples.[9]

[6] Banker et al. (2014, footnote 11) note that when uncertainty increases, "*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*."

[7] Holzhacker et al. (2015a) further argue that their findings reflect different ownership models between manufacturing firms and their sample of nonprofit and private for-profit hospitals that are associated with different forms of compensation and economic incentives (e.g., equity versus *performance based* incentives).

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

[9] A related literature focuses on the impact of uncertainty on corporate capital investments (e.g., Bernanke, 1983; McDonald and Siegel, 1986; Pindyck, 1988). This literature generally examines a binary investment decision ("wait" or "invest") under conditions of uncertainty. Studies within this literature show that, as uncertainty increases, managers are more likely to delay the amount of their irreversible investments in long-term assets to avoid investing in excess committed capacity. They will delay investing until they receive more information that reduces this uncertainty. Somewhat differently, the literature on the effect of uncertainty on cost elasticity focuses on shorter-term managerial decisions regarding the degree of cost elasticity. Unlike long-term capital investments, SG&A expenses and other operating costs (e.g., skilled indirect labor) are less irreversible and can be modified with some costs that will decrease in the long run. As stated in Banker et al. (2014, P. 847), "*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 analysis, such as skilled indirect labor. Such activity resources account for a far greater share of operating costs than physical capital, and, while fixed in the short run, they can be changed with minimal adjustment costs over a sufficiently long time horizon. Thus, irreversibility is likely to be a second-order factor in the context of activity resources central to cost behavior.*"

We now state our hypotheses:

H2a: *Cost elasticity is decreasing, on average, in the managerial perception of volume uncertainty.*

H2b: *The negative association in H2a is diminished (and may turn positive) when the congestion costs in high volume realizations are small, or the adverse consequences of losses in low volume realizations are large.*

3. Sample, variables, and descriptive statistics

3.1. Sample selection

To conduct our analysis, we begin with the sample of all firms covered by Compustat from 1996 to 2017. 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.[10] From this merged set, we exclude any firm-year observations associated with missing data, as well as any observations with 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, for each year in our sample, we remove observations in the top and bottom 1% of the respective distribution. Our final sample comprises 44,430 firm-year observations. To calculate the annual inflation rates for our sample period, we obtain monthly data from the CRSP US Treasury and Inflation database. We then use these estimates to adjust the dollar amounts of our variables for inflation. Table 1 details our sample selection procedure.

3.2. A text-based measure of the managerial perception of overall uncertainty

We construct a measure of the managerial perception of overall uncertainty based on the frequency of uncertainty-related words in the forward-looking statements (FLS) contained in the *Management Discussion and Analysis* section (MD&A) of 10-K reports. FLS provide a comprehensive view of managerial expectations regarding both ongoing and event-driven business-related aspects that may directly or indirectly impact its future financial outcomes (Loughran and McDonald, 2013). Previous studies find that the textual features of FLS can predict both current and future firm performance (e.g., Li, 2010a, 2010b; Wang and Hussainey, 2013).[11] According to Li (2010a), FLS incorporate comments related to business issues, including customer demand, competition, market conditions, liquidity, pricing, income, production, and investments. Accordingly, any uncertainty embedded in these statements can be seen as reflecting uncertainty associated with various aspects of the business and, ultimately, future firm performance. In our study, we use this measure to conduct a comprehensive analysis of the cross-sectional variation in the relation between uncertainty and cost elasticity for firms in different industries and with different firm environments.

Using a method similar to that described in Li (2010a, Appendix B), Bozanic et al. (2018, Appendix A), and Chen et al. (2019), we first extract the MD&A section of each 10-K filing and then identify the number of FLS in a given MD&A.[12] A sentence in an MD&A is classified as an FLS if it contains at least one word from the forward-looking dictionaries provided in Li (2010a) and Bozanic et al. (2018) and does not include words that indicate the sentence is legal boilerplate or refers to past events. These exclusion restrictions are needed to ensure that the sentence reflects actual and current managerial expectations. Next, we determine the percentage of *uncertain* FLS sentences using the uncertainty word dictionary provided by Loughran and McDonald (2011).[13] We identify an FLS sentence as uncertain if it contains at least one word from the Loughran and McDonald (2011) uncertainty dictionary. Prior studies have used this dictionary to examine the implications of expressions of uncertainty in various corporate 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, higher abnormal trading volume around their 10-K filing date, and greater future return volatility (Loughran and McDonald 2011). Research also shows that greater uncertainty in a firm's 10-K filing is positively associated with stricter loan contract terms (Ertugrul et al., 2017). Lastly, the level of uncertain text in a firm's 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).

[10] We omit from our sample financial institutions (four-digit SIC codes 6000–6999) and public utilities (four-digit SIC 4900–4999) as both types of firms and their corporate financial reports are mandated by industry-specific regulations. Mandatory filing through the website was phased in by the SEC over three years ending May 6, 1996.

[11] A large number of studies have documented the relation between FLS and the outcomes of future firm-related events. For example, Muslu et al. (2015) find that the quantity of FLS is higher for firms with poor information environments and thus helps investors predict 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 reactions to corporate news.

[12] 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 the FLS tone and the degree of cost stickiness and further demonstrate that managers' expectation-driven decisions can reverse any 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 perceptions of uncertainty on cost elasticity. We control for the effect of FLS tone in our regression analysis.

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

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	(47,260)
Full sample	**44,430**

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.

To measure the managerial perception of *overall* uncertainty, we compute the average uncertainty in the FLS of firm i in year t as $AVG\_FLS\_UC_{i,t}$=($FLS\_UC_{i,t-1}$+ $FLS\_UC_{i,t}$)/2 (where $FLS\_UC_{i,t}$ is the number of uncertain FLS sentences divided by the total number of FLS sentences for firm i in year t). We use the two-year average because it captures managerial forward-looking statements and their perception of uncertainty at both ends of a fiscal year, which is the unit of measurement of all the income statement variables and analysis (results are robust to using *FLS_UC* in year t only, and an average over the years t, t-1, and t-2). We then transform this variable into a continuously ranked variable scaled from zero to one and denote it as $UC\_Total_{i,t}$.

3.3. Empirical measures of the managerial perception of unit CM and volume uncertainty

To measure managerial perceptions of unit CM and volume uncertainty, we classify each uncertain FLS sentence as relating to unit CM, volume, or other uncertainty using dictionaries of terms related to unit CM and volume. We do so by inputting a list of volume and unit CM-related seed words into the *i4Semantic* machine-learning algorithm from Metaheuristica (http://www.metaheuristica.com/). The representative (seed) word lists are constructed using the terms used in reference to the category from prior research (e.g., Li, 2010a) and our subjective judgment.[14] We then use the machine learning algorithm to find the top 100 terms most similar to those in each representative list based on how the terms are used in 10-K filings.[15] We choose this machine learning approach over creating dictionaries based entirely on our judgment to mitigate subjectivity in determining the terms selected for each category. Panel A of Appendix A reports the list of words generated by the algorithm; panel B provides examples of sentences classified as relating to unit CM or volume uncertainty. From Appendix A, we see that the list of words and their use in the sample sentences support the ability of the algorithm to identify FLS sentences related to unit CM and volume uncertainty.

We then use the following steps to calculate our respective uncertainty measures of unit CM ($UC\_UnitCM_{i,t}$), volume ($UC\_Volume_{i,t}$), and other ($UC\_Other_{i,t}$): first, for each sentence classified as an uncertain FLS, we identify whether it is related to unit CM, volume, or other uncertainty. We classify a sentence as related to unit CM (volume) if it contains one or more unit CM (volume) words from the list of 100 words contextually identified by the algorithm; uncertain FLS sentences that are not classified as either unit CM or volume are categorized as "other." Next, we separately divide the number of FLS sentences classified as unit CM, volume, or other uncertainty by the sum of the unit CM, volume, and other uncertain FLS sentences.[16] We then multiply each ratio by *AVG_FLS_UC*, transform the average values of each ratio into continuously ranked variables scaled from zero to one, and denote these variables as $UC\_UnitCM_{i,t}$, $UC\_Volume_{i,t}$, and $UC\_Other_{i,t}$, respectively.

We conduct several tests to validate the ability of our text-based measures to capture the underlying constructs of unit CM and volume uncertainty. First, we examine how these text-based measures correlate with the following demand uncertainty measures from Banker et al. (2014): (1) sales variability of firm i using all available observations (UC_BBP_i) and (2) sales variability of firm i between years t-4 to t-1 ($UC\_BBP_{i,t}$).

Table 2 presents the results of our regression analyses. From Panel A, we see that our measure of volume uncertainty is positively and significantly correlated with the two *UC_BBP* measures. We further see that our measure of unit CM uncertainty

[14] The representative words are: (a) *unit CM*: cost, expense, expenses, income, margin, performance results, price, prices, pricing, profit, and reimbursement; (b) *volume*: competition, consumer demand, demand, market, market condition, market conditions, market position, new contract, revenues, and sales.

[15] The *i4Semantics* machine learning algorithm is based on the premise that "You shall know a word by the company it keeps" (Firth 1957). One challenge in identifying connections between words is that any given word occurs in many different contexts, and the context in which a 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 on the other words surrounding the given word (i.e., its context). The algorithm, implemented as a recurrent neural network, tries to solve the problem of predicting the words that surround a given word. The resulting serialization of the recurrent neural network captures the semantic representations of the words. Term similarity is then assessed as the cosine similarity of the vectors associated with a given word.

[16] An uncertain FLS sentence can include keywords from both the unit CM and volume lists, resulting in a sum of the unit CM, volume, and other uncertain FLS sentences that is greater than the number of uncertain FLS sentences. Our calculation ensures that the sum of the unranked values of $UC\_UnitCM_{i,t}$, $UC\_Volume_{i,t}$, and $UC\_Other_{i,t}$ is equal to the unranked value of $UC\_Total_{i,t}$ (see Table 3).

is not significantly associated with the two *UC_BBP* measures, *incrementally* to volume uncertainty (in a univariate regression we find that unit CM uncertainty is positively and significantly correlated with the Banker et al. (2014) measures).[17]

In our next validation test, we compare the average values of our uncertainty measures for industry concentration subsamples. As further discussed in Section 4.2 below, firms operating in highly concentrated industries possess greater market control over price, cost, and volume, and are therefore less concerned about the effects of unit CM and volume uncertainty on cost elasticity. Accordingly, we expect them to be associated with lower average values of the uncertainty measures compared to firms operating in more competitive industries. Using the Herfindahl-Hirschman Index (HHI) of market concentration, we classify industries into three types based on the level of concentration: unconcentrated (HHI<1000 until 2009 and HHI<1500 afterward), moderately concentrated (1000≤HHI<1800 until 2009 and 1500≤HHI<2500 afterward), and highly concentrated

Table 2
Validity tests of the unit contribution margin and volume uncertainty measures.

Panel A: Relation between the Uncertainty Measures and Banker, Byzalov, and Plehn-Dujowich's (2014) Measure of Demand Uncertainty

	Dependent Variable	
	UC_BBP_i	Rolling $UC\_BBP_{i,t}$
Independent Variables	(1)	(2)
$UC\_UnitCM_{i,t}$	−0.023	−0.015
	(-1.59)	(-1.04)
$UC\_Volume_{i,t}$	0.093***	0.083***
	(7.27)	(5.49)
$UC\_Other_{i,t}$	0.004	−0.004
	(0.33)	(-0.33)
Industry Fixed Effects	Yes	Yes
Adjusted R^2	0.148	0.094
N	43,793	37,467

Panel B: Average Unit Contribution Margin and Volume Uncertainty for Unconcentrated, Moderately Concentrated, and Highly Concentrated Industries

	Unconcentrated	Moderately concentrated	Highly concentrated	***t*-statistics of the differences between columns**		
	(1)	(2)	(3)	(1)–(2)	(2)–(3)	(1)–(3)
$UC\_Total_{i,t}$	0.502	0.495	0.492	1.55	0.61	2.09
$UC\_UnitCM_{i,t}$	0.504	0.498	0.470	1.39	4.49	6.82
$UC\_Volume_{i,t}$	0.507	0.472	0.475	8.47	−0.49	6.63
$UC\_Other_{i,t}$	0.492	0.524	0.538	−7.76	−2.32	−9.48
N	34,962	5581	3892			

Panel C: Spearman correlation Coefficients between the Standard Deviation of Commodity Prices and Auto Sales, and Unit CM and Volume Uncertainty

Industry	**Unit CM Uncertainty (*UC_UnitCM*)**	**Volume Uncertainty (*UC_Volume*)**
Gold (N = 114)	0.403*	0.127
Oil (N = 2,456)	0.407*	0.490**
Coal (N = 147)	0.561***	0.495**
Auto Sales (N=951)	0.057*	0.039

Panel A presents the regression of Banker et al.'s (2014) firm-level measure (column 1) and rolling measure (column 2) of demand uncertainty on the text-based measures of uncertainty. UC_BBP_i is equal to the standard deviation of the log of the change in inflation-adjusted sales by firm over the entire sample. Rolling $UC\_BBP_{i,t}$ is equal to time-series standard deviation of a log change in sales of firm *i* between years t-4 to t-1. **Panel B** reports the average values of the uncertainty measures by industry concentration. We use the Herfindahl-Hirschman Index (HHI) of market concentration, and classify industries into three types: unconcentrated (HHI <1000 until 2009 and HHI <1500 afterward), moderately concentrated (1000 ≤ HHI <1800 until 2009 and 1500 ≤ HHI <2500 afterward), and highly concentrated (HHI >1800 until 2009 and HHI >2500 afterward). These classifications are based on the U.S. Department of Justice and the Federal Trade Commission Horizontal Merger Guidelines. **Panel C** reports Spearman correlation coefficients between measures of unit CM and volume uncertainty, and the price of gold, oil, coal and volume of auto sales within the respective industries. Industries are based on the Fama-French 48 industries classification (gold (27), oil (30), coal (29), and automobiles (23)). Commodity prices are adjusted for inflation beginning in 1995 (the year prior to the start of the sample period). Standard deviations of commodity prices are calculated using the monthly prices over the sample period. Total seasonally-adjusted auto sales are from https://fred.stlouisfed.org/series/TOTALSA.
*, **, *** - Significantly different from zero at the 0.10, 0.05, and 0.01 levels, respectively. Standard errors are clustered by firm and year.

[17] The fact that *UC_BBP* is more highly related to $UC\_Volume_{i,t}$ than to $UC\_UnitCM_{i,t}$ in the multivariate regressions suggests that both *UC_BBP* and $UC\_Volume_{i,t}$ are more closely related to the variability of physical volume, consistent with the theory of congestion costs. This explanation is supported by the findings in both Banker et al. (2014) and our paper that the $UC\_Volume_{i,t}$ and *UC_BBP* measures are negatively correlated with cost elasticity, whereas $UC\_UnitCM_{i,t}$ is positively correlated with cost elasticity.

(HHI>1800 until 2009 and HHI>2500 afterward). These classifications are based on the US Department of Justice and the Federal Trade Commission Horizontal Merger Guidelines.

Consistent with our expectations, the results in Panel B of Table 2 indicate that the managerial perception of both unit CM and volume uncertainty is significantly lower in highly concentrated industries compared to unconcentrated ones. For example, the average $UC\_UnitCM_{i,t}$ ($UC\_Volume_{i,t}$) is 0.504 (0.507) in unconcentrated industries, compared to 0.470 (0.475) in highly concentrated industries (a difference of about 7% for each measure). These differences are statistically significant at the 1% level (t-statistics of 6.82 and 6.63 for $UC\_UnitCM_{i,t}$ and $UC\_Volume_{i,t}$, respectively). Moreover, we find that the correlation coefficients between the yearly measures of HHI and the annual average of our uncertainty measures across all firms in a given industry are significantly negative (untabulated).

As additional validation tests, we calculate the correlation coefficients between our unit CM and volume uncertainty measures and the standard deviations of the price of commodities, including gold, oil, and coal, as well as the average monthly automobile sales. Here, we expect the volatility in commodity prices (calculated annually using 12 monthly observations) to be positively related to the managerial perception of unit CM and volume uncertainty. This expectation is based on the notion that commodity price volatility reflects volatility in the price of raw materials and can be positively correlated with the volatility in the volume produced. Consistent with this expectation, the results in Panel C of Table 2 indicate that the correlation coefficients between our uncertainty measures and the standard deviation of the commodity prices are positive and largely significant. For example, the correlation between the unit CM uncertainty measure and the standard deviations of commodity prices ranges from 0.403 in the gold industry to 0.561 in the coal industry. Similarly, the correlation coefficient between volume uncertainty and the standard deviation of commodity prices ranges from 0.127 for gold to 0.495 for coal. Finally, we document a positive and significant correlation between the standard deviation in average monthly automobile sales and our measure of unit CM uncertainty for firms in the automotive industry.

Overall, the results of these tests provide a validation of the ability of our text-based volume and unit CM uncertainty measures to capture the underlying economic constructs.

3.4. Variable definitions

In our main analyses, our primary variables include the log change of Sales, General, and Administrative expenses (*SGA*) for firm *i* in year *t* as a dependent variable ($\Delta lnSGA_{i,t} = \log(SGA_{i,t}/SGA_{i,t-1})$), sales revenue (*REV*), and the log change of sales revenue ($\Delta lnREV_{i,t} = \log(REV_{i,t}/REV_{i,t-1})$).

Our choice of SGA as our dependent variable is motivated by the extant literature that assumes managerial resource allocation decisions are most likely to manifest themselves in the activity resources captured in SGA. In the context of our study, managerial, uncertainty-driven decisions are likely to manifest themselves in SGA as SGA expenses encompass items that are subject to managerial discretion and are costly to adjust (e.g., skilled indirect labor, rent, utilities, and insurance; see also our discussion of the results of tests using alternative measures in footnote 21).

Finally, we control for the effect of macro-economic changes using the real change in the gross domestic product (ΔGDP_t); resource adjustment costs using asset intensity ($ASINT_{i,t}$) and employee intensity ($EMPINT_{i,t}$); $ASINT_{i,t} = \log(Assets_{i,t}/REV_{i,t})$; $EMPINT_{i,t} = \log(Number\ of\ Employees_{i,t}/REV_{i,t})$, and the tone of the FLS, where $FLS\_Tone_{i,t}$ is the number of positive minus the number of negative words divided by one plus the total number of positive and negative words in the FLS.

3.5. Descriptive statistics

Table 3 provides the descriptive statistics for the non-standardized uncertainty measures and the rest of our empirical variables. From Table 3, we see that the mean (median) unranked $UC\_Total_{i,t}$ is 0.48 (0.49), indicating that about one-half of the FLS contain words related to uncertainty.[18] This total is comprised of unit CM (0.17), volume (0.19), and other (0.13) uncertainty. Consistent with the values of these variables reported in prior studies, we find that the average values of $REV_{i,t}$ and $SGA_{i,t}$ ($REV_{i,t}$ = \$2511 million and $SGA_{i,t}$ = \$445 million) are larger than their median values ($REV_{i,t}$ = \$318 million; $SGA_{i,t}$ = \$67 million). Furthermore, we see that the log change of $REV_{i,t}$, and $SGA_{i,t}$ (mean is equal to 0.05 and 0.06, respectively), and the ratio between $SGA_{i,t}$ and $REV_{i,t}$ ($SGA/REV_{i,t}$, mean = 0.28), are both similar to their values documented in prior studies.

Table 4 provides the Pearson (above the diagonal) and Spearman (below the diagonal) correlations between the main variables. From Table 4, we see that the highest degree of correlation is between $UC\_Total_{i,t}$, $UC\_UnitCM_{i,t}$, and $UC\_Volume_{i,t}$.

[18] As an important validation test of our FLS uncertainty measure, we find that the mean (median) uncertainty of sentences that are *not* classified as forward-looking is 0.14 (0.13) (untabulated). This finding suggests that statements about the past or present exhibit little uncertainty.

Table 3
Descriptive statistics.

Variable	Mean	Std. Dev.	25th Pctl	Median	75th Pctl
$REV_{i,t}$	2511	11,710	85	318	1272
$SGA_{i,t}$	445	2024	21	67	233
$\Delta lnREV_{i,t}$	0.05	0.24	−0.05	0.05	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	0.78	−0.36	0.04	0.52
$EMPINT_{i,t}$	−5.51	0.83	−5.95	−5.46	−5.03
ΔGDP_t	2.59	1.74	1.90	2.60	4.40
$FLS\_Tone_{i,t}$*	−0.22	0.24	−0.39	−0.25	−0.08
$UC\_Total_{i,t}$*	0.48	0.09	0.43	0.49	0.54
$UC\_UnitCM_{i,t}$*	0.17	0.04	0.14	0.17	0.20
$UC\_Volume_{i,t}$*	0.19	0.05	0.15	0.18	0.22
$UC\_Other_{i,t}$*	0.13	0.05	0.10	0.12	0.16

Notes:
1. This table presents descriptive statistics for the main variables used in our analysis (N = 44,430).
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 $REV_{i,t}$ [$EMPINT_{i,t} = \log(Employees_{i,t} / REV_{i,t})$]; ΔGDP_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; $UC\_UnitCM_{i,t}$, $UC\_Volume_{i,t}$, and $UC\_Other_{i,t}$ are the fraction of Unit CM, volume, and other words in uncertain FLS.
3. *, the measure is reported non-standardized. All uncertainty variables are included in the regressions are ranked to range from 0 to 1.

Table 4
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	0.02	−0.40	−0.03	−0.26	−0.14	−0.07	0.00	−0.07	0.05	−0.17	0.04
2	$SGA_{i,t}$	0.82		0.04	0.04	0.00	0.03	−0.22	−0.16	−0.08	−0.02	−0.03	0.08	−0.09	0.00
3	$\Delta lnREV_{i,t}$	−0.01	−0.01		0.66	−0.05	0.05	−0.05	0.15	−0.26	0.08	0.04	0.04	0.04	−0.01
4	$\Delta lnSGA_{i,t}$	−0.02	−0.01	0.67		0.02	0.09	−0.01	0.14	−0.31	0.10	0.05	0.04	0.06	−0.01
5	$SGA/REV_{i,t}$	−0.12	−0.01	−0.07	0.03		0.14	0.12	−0.02	0.01	−0.03	0.11	0.07	0.23	−0.10
6	$ASINT_{i,t}$	−0.04	0.01	0.03	0.09	0.10		−0.09	−0.07	−0.04	−0.08	0.01	−0.02	−0.02	0.05
7	$EMPINT_{i,t}$	−0.15	−0.10	−0.04	−0.01	0.12	−0.08		0.21	0.03	0.07	−0.02	−0.08	−0.02	0.04
8	ΔGDP_t	−0.04	−0.04	0.12	0.12	−0.03	−0.02	0.16		−0.01	0.17	−0.07	−0.09	−0.03	−0.04
9	$REVDEC_{i,t}$	0.00	−0.01	−0.21	−0.28	0.01	−0.04	0.03	0.00		−0.07	−0.03	−0.03	−0.03	0.00
10	$FLS\_Tone_{i,t}$	−0.01	0.01	0.09	0.10	−0.03	−0.09	0.07	0.16	−0.07		−0.12	−0.05	−0.04	−0.13
11	$UC\_Total_{i,t}$	−0.05	−0.04	0.03	0.04	0.11	0.01	−0.01	−0.06	−0.03	−0.12		0.73	0.74	0.34
12	$UC\_UnitCM_{i,t}$	−0.02	−0.02	0.03	0.04	0.08	−0.05	−0.07	−0.09	−0.03	−0.05	0.73		0.57	−0.13
13	$UC\_Volume_{i,t}$	−0.07	−0.05	0.03	0.05	0.23	−0.04	−0.02	−0.03	−0.03	−0.04	0.74	0.57		−0.19
14	$UC\_Other_{i,t}$	0.01	0.01	−0.01	−0.01	−0.12	0.10	0.04	−0.04	0.00	−0.13	0.34	−0.13	−0.19	

Note: This table presents pairwise Pearson (below diagonal) and Spearman correlation of our main variables. See Table 3 for variable definitions.

4. The impact of unit CM and volume uncertainty on the degree of cost elasticity

4.1. Full sample analysis

In our empirical analysis, we first test the impact of the managerial perception of overall, unit CM, and volume uncertainty on the degree of cost elasticity across our full sample of firms. We estimate the following regression model for overall uncertainty ($UC\_Total_{i,t}$)[19]

$$\begin{aligned}\Delta \ln SGA_{i,t} = {} & \beta_0 + \gamma_0 UC\_Total_{i,t} + \beta_1 \Delta \ln REV_{i,t} + \gamma_1 UC\_Total_{i,t} \Delta \ln REV_{i,t} + \nu_1 ASINT_{i,t} + \nu_2 EMPINT_{i,t} + \nu_3 \Delta GDP_t \\ & + \nu_4 FLS\_Tone_{i,t} + \left(\lambda_1 ASINT_{i,t} + \lambda_2\, EMPINT_{i,t} + \lambda_3\, \Delta GDP_t + \lambda_4 FLS\_Tone_{i,t}\right) \Delta \ln REV_{i,t} + \mu_{i,t}\end{aligned} \quad (1)$$

We estimate the following regression model to include the components of overall uncertainty ($UC\_UnitCM_{i,t}$, $UC\_Volume_{i,t}$, and $UC\_Other_{i,t}$):

[19] 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 models more quickly in Stata. Note that while all of the regressions include an intercept term, since the function does not (natively) report an intercept, we do not report the intercept terms (which is not interpretable because the models include fixed effects). Following Petersen (2009), observations in all of our regression models are clustered by firm and year to provide standard errors that are robust to cross-sectional and time-series correlations and heteroscedasticity.

$$\Delta \ln SGA_{i,t} = \beta_0 + \gamma_{0a} UC\_UnitCM_{i,t} + \gamma_{0b} UC\_Volume_{i,t} + \gamma_{0c} UC\_Other_{i,t} + \beta_1 \Delta \ln REV_{i,t} + \Big(\gamma_2 UC\_UnitCM_{i,t} + \gamma_3 UC\_Volume_{i,t} + \gamma_4 UC\_Other_{i,t}\Big) \Delta \ln REV_{i,t} + \nu_1 ASINT_{i,t} + \nu_2 EMPINT_{i,t} + \nu_3 \Delta GDP_t + \nu_4 FLS\_Tone_{i,t} + (\lambda_1 ASINT_{i,t} + \lambda_2 EMPINT_{i,t} + \lambda_3 \Delta GDP_t + \lambda_4 FLS\_Tone_{i,t}) \Delta \ln REV_{i,t} + \mu_{i,t} \quad (2)$$

From column (1) in Table 5, we see that, similar to previous studies, the coefficient estimate of the basic relation between the log change in SGA expenses and the log change in sales, β_1, is positive and significant (0.567). This result indicates that a one percent increase in sales is associated with a 0.567 percent increase in SGA expenses. In column (2) of this table, we show the results of estimating the regression in column (1) after including control variables for the level of asset intensity, employee intensity, the real change in GDP, and the overall tone of the 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). We see that the average coefficient on $\Delta lnREV_{i,t}$ remains positive and significant at 0.571 ($= \beta_1 + \lambda_1 \overline{ASINT_{i,t}} + \lambda_2 \overline{EMPINT_{i,t}} + \lambda_3 \overline{\Delta GDP_t} + \lambda_4 \overline{\Delta FLS\_Tone_{i,t}}$, reported at the bottom of the table). The results in column (3) from estimating regression equation (1), including the control variables and the interaction between the overall level of uncertainty ($UC\_Total_{i,t}$) and $\Delta lnREV_{i,t}$, indicate that the coefficient

Table 5
The impact of unit contribution margin and volume uncertainty on cost elasticity.

Coefficient	Variable	(1)	(2)	(3)	(4)
γ_0	$UC\_Total_{i,t}$			0.015***	
				(3.30)	
γ_{0a}	$UC\_UnitCM_{i,t}$				−0.003
					(-0.64)
γ_{0b}	$UC\_Volume_{i,t}$				0.024***
					(4.34)
γ_{0c}	$UC\_Other_{i,t}$				−0.002
					(-0.58)
β_1	$\Delta lnREV_{i,t}$	0.567***	0.767***	0.738***	0.726***
		(25.51)	(11.92)	(11.46)	(11.14)
γ_1	$UC\_Total_{i,t}$ * $\Delta lnREV_{i,t}$			0.052**	
				(2.62)	
γ_2	$UC\_UnitCM_{i,t}$ * $\Delta lnREV_{i,t}$				0.133***
					(5.53)
γ_3	$UC\_Volume_{i,t}$ * $\Delta lnREV_{i,t}$				−0.077**
					(-2.48)
γ_4	$UC\_Other_{i,t}$ * $\Delta lnREV_{i,t}$				0.043*
					(1.94)
Control Variables					
ν_1	$ASINT_{i,t}$		0.032***	0.032***	0.032***
			(9.23)	(9.20)	(9.21)
ν_2	$EMPINT_{i,t}$		0.002	0.002	0.002
			(0.97)	(1.02)	(1.06)
ν_3	ΔGDP_t		0.002	0.002	0.002
			(0.74)	(0.76)	(0.74)
ν_4	$FLS\_Tone_{i,t}$		0.023***	0.024***	0.023***
			(6.31)	(7.00)	(6.63)
λ_1	$ASINT_{i,t}$ * $\Delta lnREV_{i,t}$		−0.062***	−0.061***	−0.062***
			(-6.28)	(-6.26)	(-6.21)
λ_2	$EMPINT_{i,t}$ * $\Delta lnREV_{i,t}$		0.048***	0.048***	0.050***
			(4.61)	(4.67)	(4.82)
λ_3	ΔGDP_t * $\Delta lnREV_{i,t}$		0.019*	0.019*	0.020*
			(1.97)	(1.95)	(2.06)
λ_4	$FLS\_Tone_{i,t}$ * $\Delta lnREV_{i,t}$		0.055**	0.058**	0.059***
			(2.61)	(2.81)	(2.97)
Average degree of cost elasticity			0.571	0.570	0.572
Prob > F			0.000	0.000	0.000
Industry FE		Included	Included	Included	Included
Adjusted R^2		0.447	0.466	0.467	0.468
N		44,430	44,430	44,430	44,430

Notes: 1. This table presents the coefficients and the associated t-statistics (in parentheses) for the following regression model in column (3): $\Delta \ln SGA_{i,t} = \beta_0 + \gamma_0 UC\_Total_{i,t} + \beta_1 \Delta \ln REV_{i,t} + \gamma_1 UC\_Total_{i,t} \Delta \ln REV_{i,t} + \nu_1 ASINT_{i,t} + \nu_2 EMPINT_{i,t} + \nu_3 \Delta GDP_t + \nu_4 FLS\_Tone_{i,t} + (\lambda_1 ASINT_{i,t} + \lambda_2 EMPINT_{i,t} + \lambda_3 \Delta GDP_t + \lambda_4 FLS\_Tone_{i,t}) \Delta \ln REV_{i,t} + \mu_{i,t}$
and, the following regression model in column (4): $\Delta \ln SGA_{i,t} = \beta_0 + \gamma_{0a} UC\_UnitCM_{i,t} + \gamma_{0b} UC\_Volume_{i,t} + \gamma_{0c} UC\_Other_{i,t} + \beta_1 \Delta \ln REV_{i,t} + \Big(\gamma_2 UC\_UnitCM_{i,t} + \gamma_3 UC\_Volume_{i,t} + \gamma_4 UC\_Other_{i,t}\Big) \Delta \ln REV_{i,t} + \nu_1 ASINT_{i,t} + \nu_2 EMPINT_{i,t} + \nu_3 \Delta GDP_t + \nu_4 FLS\_Tone_{i,t} + (\lambda_1 ASINT_{i,t} + \lambda_2 EMPINT_{i,t} + \lambda_3 \Delta GDP_t + \lambda_4 FLS\_Tone_{i,t}) \Delta \ln REV_{i,t} + \mu_{i,t}$
2. See Table 3 for variable definitions.
3. *, **, *** - Significantly different from zero at the 0.10, 0.05, and 0.01 levels, respectively.

on the interaction between $UC\_Total_{i,t}$ and $\Delta lnREV_{i,t}$ ($\gamma_1 = 0.052$), is positive and significant. This result suggests that cost elasticity is increasing in the managerial perception of the overall uncertainty.[20]

The main focus of the analysis in this section is on estimating the effects of the unit CM and volume uncertainty on cost elasticity. Accordingly, in column (4), we replace $UC\_Total_{i,t}$ with $UC\_UnitCM_{i,t}$, $UC\_Volume_{i,t}$, and $UC\_Other_{i,t}$. The results in column (4) show a significantly positive coefficient on the interaction between $UC\_UnitCM_{i,t}$ and $\Delta lnREV_{i,t}$ ($\gamma_2 = 0.133$), indicating that a one standard deviation change in $UC\_UnitCM_{i,t}$ is associated with a 5.3% increase in cost elasticity. This finding supports the prediction in H1 and suggests that a more elastic cost function provides managers with the flexibility to respond to changes in the uncertainty about unit CM, flexibility that becomes more valuable as unit CM uncertainty increases. In support of H2a, we document that the coefficient on the interaction between $UC\_Volume_{i,t}$ and $\Delta lnREV_{i,t}$, γ_3, is negative and significant (-0.077), consistent with the congestion cost mechanism proposed in Banker et al. (2014). This result indicates that a one standard deviation change in $UC\_Volume_{i,t}$ is associated with a 3.1% decrease in cost elasticity. This finding suggests that volume uncertainty leads managers to make resource commitment decisions that *reduce* elasticity due to a concern about disproportionally high resource congestion costs under high realizations of volume.[21]

4.2. Cross-sectional analyses

To better understand managerial resource commitment decisions under uncertainty, we examine several possible determinants of the cross-sectional variation in the effect of uncertainty about unit CM and volume on cost elasticity at both the firm and the industry level. These determinants include the level of financial risk, the existence of work-in-process inventory (WiP), and the degree of industry concentration. The primary goal of this analysis is to further understand whether the negative relation between volume uncertainty and cost elasticity is diminished when the congestion costs are low, or the adverse consequences of losses in low volume realizations are greater (H2b).

We begin by estimating our main regression model for subsamples of firms facing high versus low financial risk. Similar to the argument in Holzhacker et al. (2015a), financial risk is viewed as a firm's potential inability to cover future financial obligations. This risk may result in a loss of customers and suppliers or limited access to credit and capital. Holzhacker et al. (2015a) argue that, relative to other firms, firms with high financial risk are more vulnerable to the costs associated with *low* volume realizations and should therefore prefer a more elastic cost structure. Because financial risk is likely to increase the cost associated with low volume realizations relative to the congestion costs associated with high volume realizations, we expect a high level of financial risk to moderate the negative relation between volume uncertainty and cost elasticity.

To measure financial risk, we use the Altman Z-Score (1968), which is based on the following accounting ratios that have been shown to predict corporate bankruptcy: Working Capital/Total Assets, Retained Earnings/Total Assets, Earnings Before Interest and Taxes/Total Assets, Market Value of Equity/Liabilities, and Sales/Total Assets.

Columns (1)–(4) of Table 6 report the results from estimating regression models (1) and (2) for firms above and below the median level of financial risk. As shown in columns (2) and (4), the effect of volume uncertainty on cost elasticity is negative and significant for the subsample of firms with low financial risk ($\gamma_3 = -0.142$) but is insignificant for the subsample of firms with high financial risk ($\gamma_3 = -0.067$). The difference between these two coefficients is significant at the 0.085 level. The effect of unit CM uncertainty on cost elasticity (γ_2) remains positive and significant for both subsamples (the p-value for the difference between the two coefficient estimates, 0.067, is equal to 0.108). These results are consistent with our expectation in H2b that the negative relation between volume uncertainty and cost elasticity is attenuated when the adverse consequences of losses in low volume realizations are relatively severe (e.g., when the financial risk is high). In fact, the lack of significance of γ_3 in column (4) suggests that managers of firms with a high level of financial risk are as concerned with the congestion costs associated with high volume realizations as they are with the adverse consequences of losses in low volume realizations.

Next, we estimate regression models (1) and (2) for two subsamples based on whether firms report WiP inventory (determined based on the availability of data item *INVWIP* in Compustat).[22] We use the existence of WiP inventory as a cross-sectional proxy for the importance of the congestion cost mechanism in determining the effect of volume uncertainty on cost elasticity. Since firms with WiP inventory have longer production cycles, their ability to respond to the quantity demanded in high volume realizations is reduced relative to other firms. Therefore, they are likely to be more concerned about the congestion costs associated with high volume realizations, leading them to commit in advance to a higher level of resources that are costly to adjust, such as skilled indirect labor, rent, and utilities. This decision will, in turn, reduce the elasticity of SG&A costs. Accordingly, we expect volume uncertainty to have a *greater* impact on cost elasticity for firms that report WiP inventory (the effect of unit CM uncertainty is expected to be similar across the two subsamples).

[20] 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). Accordingly, our empirical measure of elasticity might be affected by the changes in the ratio of variable to fixed costs or by a change in costs after observing the realized change in sales. Similar to the extant literature, we do not empirically distinguish between these choices.

[21] We re-estimate the regressions in Table 5 using Cost of Goods Sold (COGS) and Operating expenses (COGS and SGA combined) as the dependent variables. Consistent with the evidence in prior studies (e.g., Table 3 in Banker et al., 2014) and the inherently more variable nature of COGS (cost elasticity of 0.946 in our sample), we find that the effect of uncertainty on cost elasticity is weaker when using COGS as compared with SGA. The impact of unit CM and volume uncertainty on the operating cost elasticity is statistically significant and consistent with the signs and magnitudes reported in Table 5.

[22] Firms with WiP inventory are mostly from the manufacturing, consumer durables, and pharmaceutical sectors; the majority of firms without WiP inventory are in the retail, telecommunication, and energy sectors (based on Fama-French 12 industry classification).

Table 6
The impact of uncertainty on cost elasticity by financial risk and work-in-process inventory.

Coefficient	**Variable**	**Financial Risk**				Work-in-Process Inventory			
		Low (below median)		**High (above median)**		**None**		**>0**	
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
γ_0	$UC\_Total_{i,t}$	0.012* (1.83)		0.012** (2.25)		0.013** (2.70)		0.016*** (2.88)	
γ_{0a}	$UC\_UnitCM_{i,t}$		−0.010 (-1.70)		−0.006 (-0.74)		0.007 (1.00)		−0.016*** (-3.00)
γ_{0b}	$UC\_Volume_{i,t}$		0.029*** (3.32)		0.016* (1.87)		0.012* (1.94)		0.038*** (5.97)
γ_{0c}	$UC\_Other_{i,t}$		−0.007 (-1.42)		0.012** (2.43)		−0.001 (-0.24)		−0.002 (-0.27)
β_1	$\Delta lnREV_{i,t}$	0.584*** (3.13)	0.572*** (2.97)	0.848*** (12.24)	0.829*** (10.79)	0.808*** (9.25)	0.807*** (9.21)	0.635*** (9.15)	0.603*** (7.79)
γ_1	$UC\_Total_{i,t}$ * $\Delta lnREV_{i,t}$	0.046 (0.99)		0.051 (1.40)		0.074*** (3.34)		0.024 (0.66)	
γ_2	$UC\_UnitCM_{i,t}$ * $\Delta lnREV_{i,t}$		0.182*** (4.55)		0.115** (2.85)		0.131*** (5.34)		0.122*** (3.56)
γ_3	$UC\_Volume_{i,t}$ * $\Delta lnREV_{i,t}$		−0.142** (-2.46)		−0.067 (-1.51)		−0.041 (-1.32)		−0.112** (-2.52)
γ_4	$UC\_Other_{i,t}$ * $\Delta lnREV_{i,t}$		0.074* (1.82)		0.046 (1.39)		0.008 (0.25)		0.096*** (3.21)
Test of difference in γ_2 (*p*-value)				0.067 (0.108)				0.009 (0.438)	
Test of difference in γ_3 (*p*-value)				−0.075 (0.085)				0.071 (0.048)	
Average degree of cost elasticity		0.559	0.569	0.569	0.568	0.588	0.588	0.546	0.557
Prob > F		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Control Variables		Included	Included	Included	Included	Included	Included	Included	Included
Industry FE		Included	Included	Included	Included	Included	Included	Included	Included
Adjusted R^2		0.432	0.433	0.501	0.505	0.465	0.466	0.471	0.475
N		15,458	15,458	15,455	15,455	26,524	26,524	17,904	17,904

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

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

and, the following regression model in columns (2), (4), (6), (8):

$$\begin{aligned}\Delta\ln \mathrm{SGA}_{i,t} = \; & \beta_0 + \gamma_{0a} UC\_UnitCM_{i,t} + \gamma_{0b} UC\_Volume_{i,t} + \gamma_{0c} UC\_other_{i,t} + \beta_1 \Delta\ln REV_{i,t} \\ & + (\gamma_2 UC\_UnitCM_{i,t} + \gamma_3 UC\_Volume_{i,t} + \gamma_4 UC\_other_{i,t})\Delta\ln \mathrm{REV}_{i,t} \\ & + \nu_1 ASINT_{i,t} + \nu_2 EMPINT_{i,t} + \nu_3 \Delta GDP_t + \nu_4 FLS\_Tone_{i,t} \\ & + (\lambda_1 ASINT_{i,t} + \lambda_2 EMPINT_{i,t} + \lambda_3 \Delta \mathrm{GDP}_t + \lambda_4 FLS\_Tone_{i,t})\Delta\ln \mathrm{REV}_{i,t} + \mu_{i,t}\end{aligned}$$

Columns (1)–(4) [(5)–(8)] report the results by the level of financial risk [existence of work-in-process inventory]. To measure financial risk we use the Altman Z-score (1968), which is based on the following accounting ratios that have been shown to predict corporate bankruptcy: Working Capital/Total Assets, Retained Earnings/Total Assets, Earnings Before Interest and Taxes/Total Assets, Market Value of Equity/Liabilities, and Sales/Total Assets. We determine the existence of WiP inventory based on the availably of item *INVWIP* on Compustat. We test for the difference in coefficients between the subsamples using a bootstrap test (Shroff et al., 2014).
2. See Table 3 for variable definitions.
3. *, **, *** - Significantly different from zero at the 0.10, 0.05, and 0.01 levels, respectively.

The findings reported in columns (5)–(8) of Table 6 are consistent with our prediction in H2b. Specifically, we find that the coefficient estimate on the variable that captures the effect of volume uncertainty on cost elasticity is negative and significant ($\gamma_3 = -0.112$) for the subsample of firms that report WiP inventory but is insignificant for firms that do not report WIP inventory (the *p*-value for the difference between the two coefficients, 0.071, is equal to 0.048). As predicted, we find the effect of unit CM uncertainty on cost elasticity (γ_2) is significant and positive for both subsamples (the p-value for the difference between the two coefficient estimates, 0.009, is equal to 0.438).

Finally, we examine the effect of uncertainty on cost elasticity for subsamples based on the level of industry concentration.[23] Here, we expect that the effect of unit CM and volume uncertainty on cost elasticity is less pronounced for firms operating in concentrated versus competitive industries. Concentrated industries are characterized by superior incumbent firm technology, higher barriers to entry and consumer switching costs, greater product differentiation, economies of scale, and control over resources (see, e.g., the discussion in Tirole, 1988, page 306). Accordingly, the greater market control over

[23] As discussed above, we use the Herfindahl-Hirschman Index (HHI) of market concentration and classify industries into three types of markets: unconcentrated, moderately concentrated, and highly concentrated based on the US Department of Justice and the Federal Trade Commission Horizontal Merger Guidelines.

unit CM and volume for firms in concentrated industries should moderate managerial concerns about the effects of uncertainty on their firm's cost structure. This argument is also consistent with the theory in Caballero (1991) as well as the empirical findings in Ghosal and Loungani (1996) of a significant (insignificant) association between unit CM uncertainty and industry investment in unconcentrated (concentrated) industries.

From the results in Table 7, column (2), we see that the managerial perception of unit CM and volume uncertainty plays a significant role in cost elasticity for firms operating in unconcentrated industries (γ_2 and γ_3 are both significant, and their signs are consistent with those reported for the full sample in Table 5). By contrast, the results in column (6) show that unit CM and volume uncertainty do not play a significant role in determining cost elasticity for firms in highly concentrated industries (γ_2 and γ_3 are statistically insignificant).

The combined evidence presented in Tables 6 and 7 sheds additional light on the cross-sectional determinants of managerial resource commitment decisions under conditions of uncertainty, provides support for our main predictions, and offers additional validation of our text-based uncertainty measures.

4.3. Industry affiliation analyses

In this subsection, we examine variations in the effect of unit CM and volume uncertainty on cost elasticity based on industry affiliation. As noted earlier, two prior studies provide opposite evidence regarding the relation between volume uncertainty and cost elasticity. Using a sample of manufacturing firms, Banker et al. (2014) find a negative relation between cost elasticity and volume uncertainty (i.e., greater cost rigidity as a result of higher volume uncertainty). However, using a sample of California hospitals, Holzhacker et al. (2015a) find that a greater volume uncertainty motivates hospitals to shift to resources that are less costly to modify (measured as outsourcing, leases, and contracted labor hours), leading to greater cost elasticity. Holzhacker et al.

Table 7
The impact of uncertainty on cost elasticity by the degree of industry concentration.

		Unconcentrated		Moderately Concentrated		Highly Concentrated	
Coefficient	**Variable**	(1)	(2)	(3)	(4)	(5)	(6)
γ_0	$UC\_Total_{i,t}$	0.017*** (3.31)		0.014** (2.38)		0.010 (1.50)	
γ_{0a}	$UC\_UnitCM_{i,t}$		−0.004 (-0.71)		−0.000 (-0.02)		−0.003 (-0.32)
γ_{0b}	$UC\_Volume_{i,t}$		0.028*** (4.50)		0.010 (1.16)		0.018** (2.16)
γ_{0c}	$UC\_Other_{i,t}$		−0.004 (-0.97)		0.010 (1.03)		0.001 (0.09)
β_1	$\Delta lnREV_{i,t}$	0.797*** (12.12)	0.791*** (12.07)	0.282 (1.15)	0.255 (0.99)	0.690*** (4.93)	0.645*** (4.02)
γ_1	$UC\_Total_{i,t}$ * $\Delta lnREV_{i,t}$	0.035* (1.98)		0.140*** (4.75)		0.017 (0.21)	
γ_2	$UC\_UnitCM_{i,t}$ * $\Delta lnREV_{i,t}$		0.127*** (4.39)		0.166*** (4.68)		0.096 (1.26)
γ_3	$UC\_Volume_{i,t}$ * $\Delta lnREV_{i,t}$		−0.089** (-2.77)		−0.005 (-0.13)		−0.131 (-1.39)
γ_4	$UC\_Other_{i,t}$ * $\Delta lnREV_{i,t}$		0.041 (1.40)		0.056 (0.98)		0.060 (1.00)
Average degree of cost elasticity		0.563	0.567	0.599	0.599	0.601	0.601
Prob > F		0.000	0.000	0.000	0.000	0.000	0.000
Control Variables		Included	Included	Included	Included	Included	Included
Industry FE		Included	Included	Included	Included	Included	Included
Adjusted R^2		0.468	0.470	0.471	0.471	0.479	0.480
N		34,954	34,954	5578	5578	3888	3888

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

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

and, the following regression model in columns (2), (4), (6):

$$\begin{aligned}\Delta\ln \mathrm{SGA}_{i,t} = \ & \beta_0 + \gamma_{0a} UC\_UnitCM_{i,t} + \gamma_{0b} UC\_Volume_{i,t} + \gamma_{0c} UC\_other_{i,t} + \beta_1 \Delta\ln REV_{i,t} \\ & + (\gamma_2 UC\_UnitCM_{i,t} + \gamma_3 UC\_Volume_{i,t} + \gamma_4 UC\_other_{i,t})\Delta\ln \mathrm{REV}_{i,t} \\ & + \nu_1 ASINT_{i,t} + \nu_2 EMPINT_{i,t} + \nu_3 \Delta GDP_t + \nu_4 FLS\_Tone_{i,t} \\ & + (\lambda_1 ASINT_{i,t} + \lambda_2 EMPINT_{i,t} + \lambda_3 \Delta \mathrm{GDP}_t + \lambda_4 FLS\_Tone_{i,t})\Delta\ln \mathrm{REV}_{i,t} + \mu_{i,t}\end{aligned}$$

2. We use the Herfindahl-Hirschman Index (HHI) of market concentration, and classify industries into three types of markets: unconcentrated (HHI<1000 until 2009 and HHI<1500 afterward), moderately concentrated (1000≤ HHI<1800 until 2009 and 1500≤HHI<2500 afterward), and highly concentrated (HHI>1800 until 2009 and HHI>2500 afterward). These classifications are based on the U.S. Department of Justice and the Federal Trade Commission Horizontal Merger Guidelines.

3. See Table 3 for variable definitions.

4. *, **, *** - Significantly different from zero at the 0.10, 0.05, and 0.01 levels, respectively.

(2015a) posit that their results differ from those of Banker et al. (2014) because hospitals are likely to maintain excess capacity designed to reduce the potential for congestion costs. As a result, the congestion costs associated with an increase in volume are likely to be *lower* than the adverse consequences of losses associated with a reduction in volume.

We reexamine whether the effect of unit CM and volume uncertainty on cost elasticity differs in the healthcare and manufacturing industries.[24] We do so by using our consistently developed empirical measures of uncertainty and controlling for other types of uncertainty.

From columns (1) and (3) of Table 8, we see that γ_1 (the interaction between $UC\_Total_{i,t}$ and $\Delta lnREV_{i,t}$) is positive for both industries but significant only for the healthcare sector (0.335 versus 0.052 for the manufacturing industry). These results suggest that the opposite effects of unit CM and volume uncertainty on cost elasticity offset each other economically and statistically in manufacturing firms.

Continuing with Table 8, the results in columns (2) and (4) show that the coefficient estimates on the interactions between $UC\_UnitCM_{i,t}$ and $\Delta lnREV_{i,t}$, γ_2, are positive and significant, suggesting that unit CM uncertainty increases cost elasticity for both industries. However, we find that the coefficient estimate on the interaction between $UC\_Volume_{i,t}$ and $\Delta lnREV_{i,t}$, γ_3, is positive and significant for firms in the healthcare sector (0.208) but negative and significant for manufacturing firms (−0.128). These findings reinforce the evidence in both Banker et al. (2014) and Holzhacker et al. (2015a).

The evidence in Table 8 provides additional support for our prediction in H2b that the sign of the relation between volume uncertainty and cost elasticity is also affected by the potential magnitude of the congestion costs in high volume realizations. Moreover, it further highlights the importance of employing a consistent measurement of uncertainty and controlling for other types of uncertainty when examining the effects of unit CM and volume uncertainty on cost elasticity.

In the next subsection, we provide new evidence on the tension between the incremental and opposite effects of unit CM and volume uncertainty on cost elasticity in the healthcare and manufacturing industries.[25]

4.4. The tension between the individual effects of unit CM and volume uncertainty

In this subsection, we examine the tension between the individual effects of unit CM and volume uncertainty on cost elasticity across four combinations of the highest and lowest quintiles of unit CM and volume uncertainty for the full sample, the healthcare sector, and the manufacturing industry. Doing so, we attempt to shed additional light on the relative and incremental of each of these uncertainties on cost elasticity in the various samples. The calculations in Table 9 are based on coefficient estimates obtained from regression model (2), where the uncertainty variables are first ranked into quintiles and then transformed into a scaled-quintile variable with values ranging from zero to one in increments of 0.25 (e.g., Rajgopal et al., 2003; Amir et al., 2015).

We begin the analysis by comparing the overall elasticity when unit CM and volume uncertainty are at their highest (i.e., when both are in quintile 5) versus lowest (i.e., when both are in quintile 1) level. For both the full sample and the healthcare sector, we find significantly greater cost elasticity when both sources of uncertainties are high (e.g., 0.885 for healthcare) than when both are low (0.425). By contrast, this difference is statistically insignificant for manufacturing (0.538 versus 0.527), suggesting that when the positive effect of unit CM uncertainty and the negative effect of volume uncertainty on cost elasticity are in the highest quintile, these two forces fully negate each other in this industry. The resulting elasticity in this case is statistically similar to when both sources of uncertainty are at their lowest levels.

Next, we compare the overall elasticity when both types of uncertainty are in the opposite extreme quintiles (i.e., when one type of uncertainty is in quintile 1 and the other is in quintile 5). We find that the degree of elasticity when the positive effect of unit CM uncertainty on elasticity is in quintile 5 and the negative effect of volume uncertainty is in quintile 1 is significantly greater relative to the reverse case for both the full and manufacturing samples (e.g., 0.626 versus 0.439 for manufacturing firms, with a significant difference of 0.187). The analogous difference is insignificant in the healthcare sector (0.694 versus 0.617), suggesting that the positive effects of volume and unit CM uncertainty on cost elasticity are substitutable in this industry.

The findings in Table 9 for both the full sample and the manufacturing industry are consistent with our prediction of a tension between the positive effect of unit CM uncertainty and the negative effect of volume uncertainty in their ultimate effect on cost elasticity. The results for the healthcare sector, where both unit CM and volume uncertainty affect cost elasticity positively, indicate that cost elasticity more than doubles (from 0.425 to 0.885) when both types of uncertainty are at their highest level relative to when both are at their lowest level; this finding highlights their incremental and economically large role in shaping the cost elasticity for firms in the healthcare sector.

[24] Industry classification is based on the Fama-French 48 (12) industry portfolio for healthcare (manufacturing).

[25] In an untabulated analysis, we find that the congestion cost mechanism manifests itself in sectors that resemble manufacturing (i.e., industries with relatively high congestion costs as a result of limited capacity), such as Automobile, Recreation, Printing and Publishing, Electrical Equipment, Communication, Computers, and Measuring and Control Equipment, based on the Fama-French 48 industry classification (these sectors are not included in the manufacturing category of the Fama-French 12-industry classification used to identify the firms in Table 8). The effect of volume uncertainty on cost elasticity is negative and significant in all these industries. The congestion cost mechanism appears less relevant in other industries: Wholesale, Entertainment, Consumer Goods, and Restaurants and Hotels. In these industries, the degree of elasticity is unrelated to volume uncertainty and is positively associated with unit CM uncertainty. Consistent with the mechanism proposed in Holzhacker et al. (2015), we find that volume uncertainty is positively related to elasticity in the Tobacco Products sector. This finding suggests that these firms are more concerned about the costs associated with downward volume risk and can be reasonably attributed to tobacco companies' concern about the cost of unusually low volume realizations due to new health concerns or regulations which will reduce the number of smokers.

Table 8
The impact of uncertainty on cost elasticity in healthcare and manufacturing sectors.

		Healthcare		Manufacturing	
Coefficient	Variable	(1)	(2)	(3)	(4)
γ_0	$UC\_Total_{i,t}$	−0.019		0.013	
		(-1.11)		(1.58)	
γ_{0a}	$UC\_UnitCM_{i,t}$		−0.011		−0.018**
			(-0.38)		(-2.45)
γ_{0b}	$UC\_Volume_{i,t}$		−0.018		0.033***
			(-0.84)		(3.35)
γ_{0c}	$UC\_Other_{i,t}$		−0.025		0.003
			(-0.98)		(0.42)
β_1	$\Delta lnREV_{i,t}$	0.725**	0.652**	0.867***	0.873***
		(2.44)	(2.18)	(9.48)	(8.48)
γ_1	$UC\_Total_{i,t} * \Delta lnREV_{i,t}$	0.335***		0.052	
		(2.59)		(1.13)	
γ_2	$UC\_UnitCM_{i,t} * \Delta lnREV_{i,t}$		0.326***		0.128**
			(4.52)		(2.16)
γ_3	$UC\_Volume_{i,t} * \Delta lnREV_{i,t}$		0.208*		−0.128**
			(1.69)		(-2.35)
γ_4	$UC\_Other_{i,t} * \Delta lnREV_{i,t}$		0.049		0.143**
			(0.37)		(2.26)
Average degree of cost elasticity		0.643	0.653	0.528	0.532
Prob > F		0.000	0.002	0.000	0.000
Control Variables		Included	Included	Included	Included
Industry FE		No	No	No	No
Adjusted R^2		0.523	0.530	0.475	0.481
N		979	979	6860	6860

Notes:1. This table presents the coefficients and the associated t-statistics (in parentheses) for the following regression model in columns (1) and (3):

$$\begin{aligned}\Delta \ln SGA_{i,t} = \; & \beta_0 + \gamma_0 UC\_Total_{i,t} + \beta_1 \Delta \ln REV_{i,t} + \gamma_1 UC\_Total_{i,t} \Delta \ln REV_{i,t} + v_1 ASINT_{i,t} \\ & + v_2 EMPINT_{i,t} + v_3 \Delta GDP_t + v_4 FLS\_Tone_{i,t} \\ & + (\lambda_1 ASINT_{i,t} + \lambda_2 EMPINT_{i,t} + \lambda_3 \Delta \mathrm{GDP}_t + \lambda_4 \mathrm{FLS\_Tone}_{i,t}) \Delta \mathrm{lnREV}_{i,t} + \mu_{i,t}\end{aligned}$$

and, the following regression model in columns (2) and (4):

$$\begin{aligned}\Delta \ln \mathrm{SGA}_{i,t} = \; & \beta_0 + \gamma_{0a} UC\_UnitCM_{i,t} + \gamma_{0b} UC\_Volume_{i,t} + \gamma_{0c} UC\_other_{i,t} + \beta_1 \Delta \ln REV_{i,t} \\ & + (\gamma_2 UC\_UnitCM_{i,t} + \gamma_3 UC\_Volume_{i,t} + \gamma_4 UC\_other_{i,t}) \Delta \ln \mathrm{REV}_{i,t} \\ & + v_1 ASINT_{i,t} + v_2 EMPINT_{i,t} + v_3 \Delta GDP_t + v_4 FLS\_Tone_{i,t} \\ & + (\lambda_1 ASINT_{i,t} + \lambda_2 EMPINT_{i,t} + \lambda_3 \Delta \mathrm{GDP}_t + \lambda_4 FLS\_Tone_{i,t}) \Delta \ln \mathrm{REV}_{i,t} + \mu_{i,t}\end{aligned}$$

2. Industry classification is based on the Fama-French 48 (12) industry portfolio for the healthcare (manufacturing) industries.
3. See Table 3 for variable definitions.
4. *, **, *** - Significantly different from zero at the 0.10, 0.05, and 0.01 levels, respectively.

Table 9
Cost elasticity calculations within top and bottom quintiles of unit contribution margin and volume uncertainty.

	Volume uncertainty quintile					
	Full sample		**Healthcare**		**Manufacturing**	
Unit Contribution Margin uncertainty quintile	**1**	**5**	**1**	**5**	**1**	**5**
1	0.552***	0.499***	0.425***	0.617***	0.527***	0.439***
5	0.646***	0.592***	0.694***	0.885***	0.626***	0.538***
Differences between quintiles (1,1) and (5,5)	−0.040**		−0.460***		−0.010	
Differences between quintiles (5,1) and (1,5)	0.147***		0.077		0.187***	

Notes:1. This table presents the overall elasticity for four combinations of the highest and lowest quintiles of unit contribution margin and volume uncertainty, as well as statistical tests of differences between the categories. The calculations in are based on coefficient estimates obtained from regression model (2), where the uncertainty variables are ranked into quintiles and transformed into a scaled-quintile variable whose values range from zero to one in increments of 0.25.
2. The calculation of the overall elasticity is equal to.

$$\beta_1 + \gamma_1 UC\_UnitCM_{i,t} + \gamma_2 UC\_Volume_{i,t} + \gamma_3 {*} 0.5 + \lambda_1 \overline{ASINT_{i,t}} + \lambda_2 \overline{EMPINT_{i,t}} + \lambda_3 \overline{GDP_t} + \lambda_4 \overline{\Delta FLS\_Tone_{i,t}}$$

UC_UnitCM and *UC*_Volume are equal to zero (one) when they are in quintile 1 (5).
3. Industry classification is based on the Fama-French 48 (12) industry portfolio for the healthcare (manufacturing) industries.
4. See Table 3 for variable definitions.
5. *, **, *** - Significantly different from zero at the 0.10, 0.05, and 0.01 levels, respectively.

Taken together, the results from our analyses in Section 4 lead us to several conclusions. First, our finding that cost elasticity increases (decreases) with managerial perceptions of overall and unit CM uncertainty (volume uncertainty) is consistent with theoretical predictions. Second, this finding underscores the importance of decomposing overall uncertainty into unit CM and volume to better understand the relation between uncertainty and cost elasticity. Finally, our cross-sectional results underscore the importance of examining the contextual role of each uncertainty component in understanding the full nature of the interplay of uncertainties and their impact on a firm's cost elasticity.

4.5. Additional analyses

In addition to the robustness tests reported throughout the paper, we conduct the following analyses to validate our results (untabulated for brevity). First, we re-run our regressions using FLS uncertainty as a continuous variable and the change in the continuous variable. We also rank this variable into quintiles and transform the ranks of the uncertainty variable into a scaled-quintile variable with values ranging from zero to one in increments of 0.25. Second, we run our empirical model after incorporating the Banker et al. (2014) measures for demand uncertainty (*UC_BBP* in Table 2). Finally, to examine whether changes in elasticity stem from changes in costs or changes in prices, we control for the change in the given industry's Producer Price Index (PPI) by the North American Industry Classification System (NAICS) using data from the US Bureau of Labor Statistics. The qualitative results for the abovementioned robustness tests remain similar to those in our main analyses.

5. Conclusion

This study documents the role of the managerial perception of uncertainty in influencing a firm's cost elasticity. Understanding the relation between uncertainty and its components and cost elasticity has tangible implications because costs directly impact earnings. Moreover, evidence in prior studies indicates that understanding a firm's cost structure allows us to obtain new insights on financial accounting topics such as predicting future earnings, analyzing the properties of analyst earnings forecasts, and explaining accounting conservatism (see, e.g., the review by Banker et al., 2018).

Using the percentage of forward-looking statements in 10-K reports containing uncertainty words as our measure of the managerial perception of overall uncertainty, we find that cost elasticity increases in our measure of total uncertainty. Importantly, we find that the degree of cost elasticity increases in the managerial perception of the unit CM uncertainty but decreases in the managerial perception of volume uncertainty. Examining our results by industry affiliation, we find a negative association between volume uncertainty and cost elasticity for manufacturing firms but a positive association for firms in the healthcare sector. We further document an economically meaningful variation in these effects based on firm characteristics and the level of industry concentration. Our findings are consistent with theoretical predictions, and underscore the importance of decomposing overall uncertainty into unit CM and volume, as well as considering industry affiliation and firm characteristics to better understand the relation between uncertainty and cost elasticity.

In conclusion, this study advances our understanding of the determinants of firms' cost elasticity in various contexts and can thus assist decision-makers in shaping a firm's cost structure. Moreover, it illustrates how understanding the textual properties of corporate financial disclosures can enhance our understanding of managerial resource allocation decisions. We hope that future work will explore other determinants of cost structure and exploit additional features of financial reports to advance our understanding of questions traditionally deemed as pertaining to managerial accounting research.

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Appendix A

Panel A: List of words generated by the *Metahueristica* algorithm

Price (Contribution Margin)		**Volume (Product Demand)**	
price	historical_highs	demand	oversupply
prices	reimbursable	market	pricing_pressure
pricing	sg&a	competition	Larger
cost	very_volatile	revenues	dominates
expense	payer	sales	compete_favorably
expenses	fees	consumer	encounters_competition
income	medical	conditions	cyclical
margin	commodity_prices	compete	existing
profit	procedural_terminology	intense_competition	markets
reimbursement	taxable	highly_competitive	highly_fragmented
performance	hospital_inpatient	contract	shipments
results	increasingly_scrutinizing	new	Fierce
payors	medically_necessary	competing	Prices
payers	record_highs	extremely_competitive	Selling
reimbursed	priced	position	Many
Tax	volatile	condition	Comes
margins	lower	competes	gross_margins

(*continued*)

Panel A: List of words generated by the *Metahueristica* algorithm

Price (Contribution Margin)		**Volume (Product Demand)**	
payor	cost_containment	competitors	technological_advances
incurred	cpt_code	face_intense	faces_strong
increasingly_challenging	payors_determination	faces_competition	gross_margin
taxes	fluctuated_widely	face_competition	gross_profit
administrative	historic_highs	competitive	cyclicality
increasingly_attempting	unapproved_indication	intense	product
costs	indigent	intensify	growing
purchase	healthcare_payers	compete_effectively	overcapacity
medicaid	reimbursing	revenue	intensifies
Net	highs	entrants	distributors
spread	drg (diagnosis-related group)	faces_intense	contracts
medicare	headcount	intensely_competitive	marketplace
medicare_medicaid	healthcare_reforms	compete_successfully	marketing
medicare_reimburses	experimental_unnecessary	low_barriers	Upturn
medicares	depressed	faces	increased
Hcfa	fluctuate_widely	intensified	primarily
medicaid_programs	gross_margin	competed	volumes
physicians_hospitals	hospital_inpatients	few_barriers	Results
managed_care	depreciation	fragmented	heavily_influenced
reimbursements	mix	competitive_pressures	volume
cpt_codes	medicaid_recipients	barriers	commercial
amortization	formularies	much_larger	especially
extremely_volatile	salaries_wages	competitor	highly_cyclical
earnings	indigent_patients	faced	customers
basis_points	nontaxable	dominate	downturns
salaries	unnecessary_inappropriate	pricing_pressures	essentially_flat
administration_hcfa	cms (centers for medicare & medicaid services)	dominant	economy
medicare_beneficiaries	libor_plus	industry	distributor
hospital_outpatient	volume	consumers	price
reimburse	healthcare	intensified_competition	shifting
healthcare_providers	hospitals	dominated	consumer_spending
volumes	balanced_budget	competitive_landscape	slowdown
market	rulings_interpretations	vigorous_competition	cyclical_nature

Panel B: Examples of price uncertainty FLS sentences

With the recent drop in oil prices, there is a **possibility** that the cost of imported gas may decline, which in turn may cause the Polish regulator to decrease the **cost** of gas sold by POGC and thereby reduce the price POGC pays to us.

Additionally, we **anticipate** that our **gross margin** will increase as we will be able to obtain better **pricing** terms from our suppliers and achieve further economies of scale as a result of purchasing larger quantities of products. However, in order to increase sales volume we may lower our **prices** and therefore may maintain our **margins.**

This distribution channel is **anticipated** to provide higher contribution **margins** as compared to royalty revenues from a partnership.

The results of these investigations and reviews **may** result in additional settlement payments or reductions in **reimbursements** for certain tests.

The Company continues to expect commodities and related **pricing** to remain **volatile** in 2007.

While it remains difficult to **predict** future natural gas **prices,** in order to reduce the risks associated with volatile prices, we use a variety of techniques, which include reducing consumption through improved manufacturing processes, switching to alternative fuels and hedging.

Panel C: Examples of volume uncertainty FLS sentences

As regulations restricting materials in electronic **products** continue to increase around the world, there is a **risk** that the cost, quality and manufacturing yields of **products** that are subject to these restrictions, may be less favorable compared to products that are not subject to such restrictions, or that the transition to compliant products may not meet customer roadmaps, or produce sudden changes in **demand**, which may result in excess inventory.

If any of our **competitors** were to introduce superior software products at **competitive** prices, or if our software products no longer met the needs of the **marketplace** due to technological developments and emerging industry standards, our software products **may** no longer retain any significant **market** share.

We **believe** the weakened industry **demand** in 2006 and into early 2007 was due, in part, to concerns from **consumers** over rising interest rates, higher minimum credit card payments and increased fuel costs, all of which contributed to the deferral of tire purchases.

In order to meet increased **demand** and maintain our **market** share, we **may** need to increase production, which could require us to build new facilities, expand our existing facilities, purchase additional manufacturing equipment, and add qualified staff.

We expect **revenue** from our indirect **sales** channel and, accordingly, our **dependence** on **distribution** partners, to continue to increase as we establish relationships with companies to resell our software worldwide.

Because the e-commerce industry is highly **competitive** and has low **barriers** to entry, we **may** be unable to compete effectively.

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