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Price Rigidities and the Value of Public Information

Lifeng Gu
The University of Hong Kong

Jin Xie
Peking University

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Keywords: Nominal Rigidities, Information Frictions, Public Information, Capital-Market Efficiency.
JEL Classification: E12, E44, G28, G32, G33.

Peking University HSBC Business School University Town, Nanshan District Shenzhen 518055, China

Price Rigidities and the Value of Public Information*

Lifeng Gu[†] Jin Xie[‡]

May 19, 2022

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[†]HKU Business School, The University of Hong Kong. Email: oliviagu@hku.hk.

[‡]HSBC Business School, Peking University. Email: jinxie@phbs.pku.edu.cn.

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Raw materials prices have surged. Corporate profits are likely next. (*Wall Street Journal,* April 12, 2021)

Sleep Number Corp., the Minneapolis-based mattress seller, has already decided to increase prices this year to offset the higher cost of certain chemicals ... The company has contracts in place that delay the timing of when its foam suppliers can pass on higher input prices. But the company nonetheless expects to feel an impact ... Sleep Number declined to disclose additional details about its plans to raise prices. (*Wall Street Journal,* March 8, 2021)

1. Introduction

Amid the COVID-19 pandemic, federal stimulus, vaccinations, and ultimately boosted demand have led to a market-wide fear of inflation. As in the *Wall Street Journal* quotes above, although prices for raw materials are surging, companies are raising product prices with a considerable time lag. Even worse, managers often keep their plans for price changes confidential. As such, Wall Street can be left playing guessing games about what next season's earnings profiles will look like.

This real-life phenomenon raises two important questions: First, does output-price inflexibility exacerbate information friction in the stock market? Second, does public information regarding firm value mitigate such information friction? Despite a growing consensus that both output-price inflexibility and the financial market propagate and amplify shocks to the macro-economy, most theoretical works in this line of literature assume zero interaction between real frictions in product and capital markets in shaping business cycles. Bernanke et al. (1999), for example, implicitly assume that irrespective of how imperfect the capital market is, firms with differential output-price inflexibility face the same imperfection. In contrast to this assumption, recent studies document that price rigidity is an important determinant of equity premium, return volatility, and leverage (Li and Palomino, 2014; Weber, 2015; Gorodnichenko and Weber, 2016; D'Acunto et al., 2018).

We conjecture that firms' inability to adjust output prices suppresses the revelation of firm-value-related information, such as information on cost shocks, and thereby exacerbates information asymmetry. If a firm is hit by a cost shock, outsiders cannot costlessly observe

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the firm's marginal cost unless price is fully adjusted and, as a result, do not know the firm's optimal reset price and profit margin. Compared with flexible-price firms, inflexible-price firms change prices less frequently and firm outsiders rely more on private information about costs to predict future firm profits. However, public information about changes in input costs could bridge the information gap by increasing the information precision of outsiders' private views. This intuition suggests the following hypothesis: output-price inflexibility exacerbates information asymmetry, and public information about firms' input-cost structure mitigates such information asymmetry.

To measure output-price inflexibility, we use the frequency of price adjustment (FPA) for each granular North American Industry Classification System (NAICS) sector provided by Pasten et al. (2017). The authors use the confidential microdata underlying the Producer Price Indexes (PPIs) from the Bureau of Labor Statistics (BLS). On the sample period from 2002 to 2012, the authors aggregated the frequencies of price adjustment at the goods level into NAICS sectors of different granularities. Consistent with a large literature in macroeconomics, D'Acunto et al. (2018) verify that output-price inflexibility is a persistent feature.[1]

To test the hypothesis, we construct a novel form of public information to quantify the time-varying visibility of firms' input costs. More specifically, we use the combination of the input-output (IO) tables at the Bureau of Economic Analysis (BEA) and monthly PPIs published, or discontinued, by the BLS, both of which are at the level of granular NAICS sectors. The BLS decides which price indices should be publicized, via a resampling process conducted at the 6-digit NAICS level. Within each sector, both the types and numbers of product indices disclosed through this resampling process vary over time. Thus, the input-cost visibility measure for each customer sector is time varying. For each customer sector j, we measure the extent to which information about the sector's input-costs is publicly available, by averaging the publication record of product indices across all j's supplier sectors. To differentiate the importance of each supplier sector i to customer sector j, we weight i's

[1]The authors find a firm-level regression of post-1996 price flexibility on pre-1996 price flexibility yields a slope coefficient of 0.93.

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publication status using a sector-by-sector matrix to construct the input shares for a customer sector j. The input-share measures the extent to which a supplier sector i contributes to a one-unit output produced by customer sector j.

The following hypothetical example illustrates how we construct the input-cost visibility for the automotive sector as of January, 1997. Suppose car manufacturers in the automotive sector (customer sector) purchase intermediate goods from three supplier sectors: steel, aluminum, and glass. The dollar amounts these supplier sectors sell to the automotive sector are respectively 30%, 20%, and 50% of the total production of cars. Meanwhile, suppose 90%, 80%, and 50% of price indices in steel, aluminum, and glass sectors, respectively, are published by the BLS. The automotive sector's input-cost visibility as of January 1997 is 0.68 (30%×90%+20%×80%+50%×50%).

One might argue that by analyzing accounting numbers, outsiders learn about the firm's input costs. For two reasons, however, investors must draw inference from other publicly available information (e.g., survey-based data disclosed by statistical agencies) that would bear on the firm's costs. First, accounting information is incomplete and noisy either because of historical-cost-accounting attributes or because managers are either not able or are unwilling to communicate all private information in financial statements (Graham et al., 2005).[2] Second, the PPI-based visibility measure is updated monthly and provides real-time information about a customer sector's input costs, whereas the disclosure of financial statements has been less frequent and much delayed.

We perform empirical analysis on the S&P 1500 constituent firms over the sample period from July 1997 through June 2013. Following prior literature, we proxy information asymmetry with the bid-ask spread (e.g., Leuz and Verrecchia, 2000; Wittenberg-Moerman, 2008), the probability of informed trading (PIN; e.g., Easley et al., 2002; Duarte and Young, 2009; Duarte et al., 2020), and analyst forecast dispersion (e.g., Diether et al., 2002; Johnson, 2004). Consistent with our conjecture, output-price inflexibility is positively associated with all empirical measures of information friction, if we hold input-cost visibility at zero. Specif-

[2]Firms often keep their cost information confidential for a variety of strategic motives. For example, public firms often ask the US Securities and Exchange Commission (SEC) to redact prices in procurement contracts that have to be disclosed in financial statements (Verrecchia and Weber, 2006).

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ically, holding input-cost visibility at zero, a one-standard-deviation increase in output-price inflexibility is associated with a 12%, 17.5%, and 7.5% increase in the bid-ask spread, PIN, and forecast dispersion of the corresponding sample means. However, public information on input-cost significantly reduces information friction for inflexible-price firms. Specifically, for fully inflexible-price firms, a one-standard-deviation increase in input-cost visibility reduces the bid-ask spread, PIN, and forecast dispersion by 12.1%, 19.7%, and 11.3% of the corresponding sample means, whereas for fully flexible-price firms, an increase in input-cost visibility does not mitigate information asymmetry. Our results are robust to the inclusion of a set of controls proposed by D'Acunto et al. (2018), year-, and firm-fixed effects, and to a broad array of checks.

One concern is that the BLS's publication, or discontinuation, of price indices for supplier sectors might be correlated with unobservable, time-varying economic conditions at the level of a customer sector. To address endogeneity, we employ a panel instrumental variable (IV) strategy that utilizes a quasi-natural experiment in which, by a single exogenous event in January, 2004, the Office of Publications at the BLS switched from the 1987 Standard Industrial Classification (SIC) system to the NAICS system, extending the publication domain into many newly emerged sectors under the NAICS system. As such, different customer sectors experienced differentially sizable changes in cost visibility, because suppliers of the same customer sector experienced different changes in publication coverage. Our main findings are robust to the panel-IV strategy, suggesting the component of cost visibility uncorrelated with firm fundamentals mitigates inflexible-price firms' information frictions.

Several additional findings also support our intuition that output-price inflexibility suppresses the revelation of firm-value-related information and thereby exacerbates information asymmetry. First, we examine whether security analysts inquire about more cost-related information during conference calls of inflexible-price firms. To do so, we perform textual analysis on transcripts of conference calls to measure the extent to which sophisticated outsiders — analysts participating in the call — request more information about production costs of a hosting company. On a sample of about 40,000 conference-call transcripts, we

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textually extract questions that analysts ask during the Q&A session regarding material information about the hosting company's costs. We identify cost-related questions if costs and expenses related to a firm's production process are explicitly mentioned in the question (e.g., "Can you tell us a little bit about how you expect your material costs to trend?"). We find evidence that analysts ask many more such questions if inflexible-price firms host the conference calls.

Second, we test whether the stock-market pricing of earnings news during announcement differs between firms with differential output-price inflexibility. We find investors react more strongly to earnings news announced by inflexible-price firms, suggesting that earnings news provides a higher incremental contribution to these firms' stock-price discovery process. Moreover, we fail to detect any systematic difference in post-earnings-announcement drifts between inflexible- and flexible-price firms, indicating the differential initial stock-market reactions are not explained by investors of inflexible (flexible) firms being less (more) constrained by the transaction costs of trading on earnings news.

Finally, we explore whether managers of inflexible-price firms tend to issue more earnings guidance. Specifically, we exploit staggered adoption of the universal demand (UD) law, which exogenously reduced managerial perceived litigation risk on corporate disclosure. We document that after the adoption of the UD law, inflexible-price firms issued more earnings guidance than before and relative to flexible-price firms. Such evidence suggests inflexible-price firms are subject to greater information asymmetry and that such firms enjoy greater benefits from disclosing earnings information.

1.1. Related Literature

Our paper makes several contributions. First, our study adds to the growing literature on the connection between firms' product-pricing strategy and capital-market outcomes.[3] Li and Palomino (2014) and Weber (2015) analyze the asset-pricing implications of output-price

[3] Price rigidity is one aspect of adjustment inflexibility. Recent contributions studying asset pricing and corporate finance implications of other aspects of adjustment inflexibility are Favilukis and Lin (2016a), Favilukis and Lin (2016b), Gu et al. (2018), and Gu et al. (2020).

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inflexibility. Gorodnichenko and Weber (2016) show that after monetary-policy announcements, the conditional volatility of stock market returns increases more for inflexible-price firms. D'Acunto et al. (2018) document that inflexible-price firms tend to adopt lower financial leverage. Xie (2020) examines capital-market consequences of asymmetric output-price rigidities. Li et al. (2021) develop a general-equilibrium model to account for the moderating effects of securities regulation on debt-market frictions through the lens of managerial misreporting. Our study departs from the prior literature by explicitly testing the connection between price rigidities and information friction. In particular, we propose a novel channel through which output-price inflexibility exacerbates information asymmetry.

Peress (2010) shows firms insulate profits by using monopoly power to pass on economic shocks to customers, which encourages risk-averse investors to trade and expedites the incorporation of their private information into stock prices. We find flexible-price firms directly reveal value-related information through price adjustments.

Second, our paper speaks to the literature studying the effect of public information disclosure. In the economic literature, Morris and Shin (2002) and Morris et al. (2006) show the release of public information might be detrimental to social welfare if agents, because of coordination motives, overweight public signals or rely less on their own private signals. Amador and Weill (2010) show that a public release of economic statistics provides new information but also increases uncertainty about monetary-policy shock.

The role of public information has also been studied in the finance and accounting literature to understand a variety of financial-market phenomena. Kim and Verrecchia (1991) investigate theoretically how the price and volume (over) react to a public announcement. Bushman (1991) analytically shows the value of public information to stock traders varies with the structure of the private-information market. Morris and Shin (2004) and Gao and Jiang (2018) analyze the role of public signals on bank runs. Goldstein and Sapra (2013) discuss the pros and cons of banks' disclosure of stress-tests to promote financial stability. In different hypothetical economies, Allen et al. (2006), Gao (2008a), Gao (2008b), and Chen et al. (2014) identify conditions under which public information increases or decreases

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stock-market efficiency, cost capital, welfare, and price informativeness. Chen et al. (2017) examine uniform and discretionary regimes for reporting information about firm performance from the perspective of a standard-setter, in a setting where the reported information can help coordinate decisions by users of the information.

A large body of empirical work examines the impact of various sources of public information on information asymmetry and capital-market efficiency. The first example of such a source is the media. Fang and Peress (2009), Peress (2014), and Guest (2021) document evidence consistent with media coverage of stocks improving the dissemination of information among investors and its incorporation into stock prices. Bushman et al. (2017) find the media coverage of borrowers fundamentally alters the information structure and the nature of competition in the loan market. In contrast to the above view, Bushee et al. (2010) and Fang et al. (2014) find the massive media coverage of stocks leads to worse investment outcomes due to agents' limited attention. The second example is the supply of public information caused by a change in regulation standards. Aytekin et al. (2017) and Kang et al. (2021) document that greater loan-level transparency reporting rules (enforced by regulators) improve banks' credit practices and internal decision-making. Hertzberg et al. (2011), however, show public information exacerbates lender coordination. The third example is corporate earnings news. Beginning with Ball and Brown (1968), although a large literature documents the positive role of publicly announced earnings in the process of stock-price recovery, the relative importance of the surprise content of earnings announcements in providing new information to the stock market is still the subject of debate (e.g., Ball and Shivakumar, 2008). Easton et al. (2009) and Bushman et al. (2010) show earnings news contains value-relevant information for corporate bond and syndicated loans. The fourth example is analysts' recommendation. Gleason and Lee (2003) and Piotroski and Roulstone (2004) document analysts' contribution to improving the speed and efficiency of the price formation process. De Franco et al. (2009, 2014) document the informational role of analysts in the debt market. By contrast, Guo et al. (2020) find that analysts' biased recommendations could be a source of market friction that impedes the efficient correction of mispricing.

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Our study explores this topic in the context of firms' product pricing. We construct a novel form of public information regarding a specific driver of firm value using economic statistics disclosed by the government. We find such public release has direct beneficial effects for investors of inflexible-price firms by providing new information but might have exacerbated information asymmetry among investors of flexible-price firms, who frequently observe price adjustments.

2. Conceptual Framework and Hypotheses

We establish a conceptual framework and develop testable hypotheses to guide our empirical analysis. Specifically, we illustrate how output-price inflexibility exacerbates information asymmetry and how public information about firms' value mitigates such information asymmetry more for inflexible-price firms.

Our price-setting framework is closest in spirit to Ball and Mankiw (1994) and most recently Gopinath and Itskhoki (2010). Consider a profit-maximizing firm whose economic life consists of multiple price cycles. Each cycle consists of two periods – an even period (t) and an odd period (t+1). The firm can freely change its price at the beginning of each cycle, but it has to pay a cost to adjust in the middle of the cycle. This cost should be interpreted broadly as not only the cost of reprinting a menu with new prices, but also of collecting and processing information, bargaining with suppliers and customers, and so on (see Gorodnichenko and Weber, 2016). By definition, inflexible-price firms bear higher costs than flexible-price firms to adjust price. A firm refuses to adjust product prices, because the cost of adjusting exceeds the gain from doing so. We consider two scenarios in which the firm receives different economic shocks that affect firm value.

Scenario 1: The firm receives a privately observed input-cost shock at the end of period

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t, but output-price changes are publicly observed.[4] A flexible-price firm will re-optimize profits by changing its price according to the sign and magnitude of the cost shock; an inflexible-price firm, by contrast, keeps its price constant.

If the firm resets price accordingly, outsiders could back out information related to the cost shock from price changes. If the firm does not reset price to the cost shock, each outsider forms her own view regarding the state of the shock. Information friction comes from a subjective error specific to each outsider (Woodford, 2003). The cross-individual differences in subjective errors might come from either investors' limited capacity (e.g., Sims, 2003) or their lack of incentives to collect and process information (e.g., Coibion et al., 2018).

Because outsiders are not equally informed (quality of their own private views about the cost shock is different), information asymmetry between firm insiders and outsiders naturally translates into information asymmetry among outsiders. Thus, information asymmetry is more severe between firm insiders and outsiders and also among outsiders of inflexible-price firms regarding the firm's profit margin in the $t+1$ period. If parameters governing the firm's demand curve is publicly known, this prediction on profit margin can be extended to firms' future profits.[5]

Public information about firms' input-cost structure can increase the information content of outsiders' observation of the state of a shock and thereby reduce their cost of collecting and processing information. Thus, the aforementioned subjective error due to outsiders' heterogeneous capacities and incentives in information collection and processing will be reduced, which in turn mitigates information asymmetry between firm insiders and outsiders and also information asymmetry among outsiders. This intuition leads to the following hypothesis:

[4]We adopt a realistic assumption that output prices are publicly observable but firms receive privately observed cost shocks (e.g., Rotemberg and Saloner, 1986; Athey et al., 2004). As for prices, investors could have easy access to price quotes by visiting a firm's websites and retail stores, checking price items of commonality futures, and talking to sales representatives. As for costs, firms often strategically withhold cost information from the public, including the cost composition of raw materials, state-of-art technologies, and bargaining powers over stakeholders.

[5]To illustrate, the firm's demand curve at period t is given by: $Q_t = BP_t^{-\rho},\ B > 0,\ \rho > 1$, where P is the nominal price per unit of output, and B and ρ are market size and demand elasticity, respectively. Assume the nominal input cost per unit is C_t. The initial optimal selling price at period t is $P_t^* = \Lambda \times C_t$, where $\Lambda = \frac{\rho}{\rho-1} = \overline{\rho} > 0$ is a constant rate of markup.

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Hypothesis 1: *Output-price inflexibility exacerbates information asymmetry, and public information about firms' input-cost structure mitigates such information asymmetry.*

Scenario 2: The firm receives a privately observed demand shock at the end of period t, which is triggered by a change in consumer preference (i.e., ρ in footnote 4). Again, output-price changes are publicly observed. If the demand shock is positive (negative), the firm increases (reduces) the markup per unit afterwards. The firm's input cost per unit stays constant after the demand shock.[6]

If the firm adjusts price accordingly to the demand shock, outsiders can back out information on the firm's quantity to be sold in period $t+1$. If the firm fails to adjust prices to demand shocks, each outsider forms her own view about the firm's future quantity to be sold. Thus, information asymmetry is more severe among outsiders of inflexible-price firms regarding the firm's future quantity to be sold. Because the firm's input cost per unit is fixed and publicly known, the prediction about information asymmetry on firms' quantity to be sold can be extended to firms' future profits. Public information on demand shock can increase the information precision of outsiders' private views, which in turn decreases disagreement among outsiders. This intuition leads to the following hypothesis:

Hypothesis 2: *Output-price inflexibility exacerbates information asymmetry, and public information about firms' demand mitigates such information asymmetry.*

Because both the input-cost shock and demand shock in scenarios 1 and 2 are firm-value-related economic shocks, we can generalize our hypothesis as follows:

Hypothesis 3: *Output-price inflexibility exacerbates information asymmetry, and public information about firms' value mitigates such information asymmetry.*

However, if only a small set of sophisticated outsiders have the ability to gauge the mapping between firms' price changes and economic shocks, information asymmetry is not necessarily lower for flexible-price firms. Similarly, if only some sophisticated outsiders can interpret the cost or demand information from a public disclosure, such public information can not necessarily reduce information asymmetry. These arguments suggest alternative null

[6]Taking the logarithm of both sides of the demand curve, we get $log(Q_t) = log(B) - \rho \times log(P_t)$. According to $P_t^* = \Lambda \times C_t$, a negative (positive) shock to ρ increases (decreases) P_t^*. By adjusting price to P_t^*, a flexible-price firm reveals the shock to ρ to the public and, hence, investors back out Q_t^*.

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hypotheses. Because public information on firms' demand is difficult to obtain, we focus our empirical analysis on hypothesis 1.

3. Data and Measures

3.1. Producer Price Index (PPI) Program at the BLS

On a monthly basis, the BLS collects prices from about 25,000 establishments for approximately 100,000 individual items. The BLS defines PPI prices as "net revenue accruing to a specified producing establishment from a specified kind of buyer for a specified product shipped under specified transaction terms on a specified day of the month."[7] Each PPI is an aggregation of prices for individual items.[8] Every seven to eight years, the BLS selects a new sample of establishments within a sector to keep up with the trend. This resampling occurs to account for changes in the industry structure and changing product market conditions within the industry. Through the resampling process, indices corresponding to new products with a sufficient number of price quotations are naturally added to the PPI program.

Product indices also go out of publication if they fail to meet either of the two following conditions. First, the index must have cooperation from a minimum number of reporting units. Second, in any given month, the index must have actual prices from a minimum number of reporting units.

3.2. Output-Price Inflexibility

To measure output-price inflexibility, we use a proprietary dataset provided by Pasten et al. (2017). Using the confidential microdata underlying the PPI program from 2002 to 2012, the authors calculate the FPA as the ratio of the number of price changes to the total number of

[7]See Chapter 14, BLS Handbook of Methods, available under http://www.bls.gov/opub/hom/.

[8]The BLS follows the following three procedures to determine the individual goods to be included in the PPI. First, the BLS selects establishments using a systematic sampling from a listing of all firms that file with the Unemployment Insurance System. Second, the BLS combines individual establishments within the same industry. Third, after a firm is selected and agrees to participate in the survey, a probability-sampling technique called disaggregation is used to determine which specific products or services will be included.

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sample months.[9] The authors then aggregate goods-based frequencies into 674 data points at the level of 6-digit NAICS sectors and 352 data points at the level of 5-digit NAICS sectors, respectively.

The data are consistent with the finding by Nakamura and Steinsson (2008) that a median duration of prices is between 8 and 11 months. FPA measures the mean fraction of months with price changes during the sample period à la Calvo (1983) and is time invariant.[10]

3.3. Bureau of Economic Analysis Input and Output Tables

The BEA produces benchmark IO accounts using Census data. The I-O accounts show how industries interact; specifically, they show how industries provide input to, and use output from, each other to produce gross domestic product (GDP). The BEA defines industries at two levels of aggregation, comprehensive updates (detailed accounts) and annual updates (summary accounts). Comprehensive updates, which are typically conducted at five year intervals, tend to have a more expansive scope than annual updates and provide an opportunity to update the accounts to better reflect the evolving US economy. To mitigate concerns about unobserved heterogeneity across granular sectors within the same coarsely defined industry, we use the comprehensive updates.[11]

The IO accounts consist of a "make" table and a "use" table. The make table shows the production of commodities by industry. In the make table, the rows document the output products each industry produces. The use table shows the uses of commodities by intermediate and final users. In the use table, the columns document the input products each industry uses. The structure of the demand of intermediate input and supply remains stable from year to year. We follow Badertscher et al. (2013) to forward file the detailed IO tables every five years. Specifically, we utilize the 1997, 2002, and 2007 IO tables from the

[9]For example, if an observed price path is $5 for three months and then $10 for another two months, one price change occurs during five months, and the frequency is 1/5.

[10]We match FPA to Compustat firms based on the 6-digit NAICS sector codes. If Compustat firms' 6-digit NAICS codes are not matched with those in the adjustment-frequency data, we switch to using 5-digit codes. We repeat the procedure of using less granular industry codes as surrogates until 3-digit codes.

[11]In Tables A.2 and A.7, we also show our results are robust to using the annual updates to measure input-cost visibility.

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comprehensive updates to construct sector-by-sector matrixes for the periods of 1997-2001, 2002-2006, and 2007-2011, respectively.

We follow the three-step method developed by Ozdagli and Weber (2018) to construct the corresponding share of inputs a customer sector purchased from each supplier sector. We illustrate the procedure in Table 1 with a hypothetical economy that only consists of two sectors: farm and forestry.

In the first step, we use the make table (MAKE), which is a sector-by-commodity matrix, to determine the share of each commodity c that each supplier sector i produces.[12] We calculate the market share of supplier sector i's production of commodity c as

$$SHARE = MAKE \odot (\mathbb{I} \times MAKE)^{-1}_{i,j}, \tag{1}$$

where $\mathbb{I}$ is a matrix of 1's with suitable dimensions. As the first step of Table 1 shows, because the farm (forestry) sector produces 900 (100) farm-related commodities and 100 (900) forestry-related commodities (see the make table), the farm (forestry) sector's market shares in the two types of commodities are 90% (10%) and 10% (90%), respectively.

In the second step, we multiply the share and use table (USE) to calculate the dollar amount that supplier sector i sells to customer sector j. This matrix is a supplier sector-by-consumer sector matrix:

$$REVSHARE = (SHARE \times USE). \tag{2}$$

In the second step of Table 1, because the farm (forestry) sector uses 200 (800) farm-related commodities and 800 (200) forestry-related commodities (see the use table), the farm sector sells 260 (200 $\times$ 90% + 800 $\times$ 10%) to the farm sector; the forestry sector sells 740 (200 $\times$ 10% + 800 $\times$ 90%) to the farm sector. Applying a similar method, the farm forestry supplier sectors sell 740 and 240, respectively, to the forestry customer sector.

In the third step, we use the revenue-share matrix to calculate customer sector j's inputs

[12] Due to data unavailability for output-price movements, we exclude the following intermediate industries: federal general government (defense, non-defense, and enterprises), state and local general government, state and local government enterprises, scrap, used and secondhand goods, and noncomparable imports and rest-of-the-world adjustment.

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purchased from supplier sector i *as a percentage* of total output of sector j. The resulting matrix is labeled $SUPPSHARE$:

$$SUPPSHARE = REVSHARE \odot ((MAKE \times \mathbb{I})^{-1}_{i,j})^{T}. \tag{3}$$

A straightforward calculation in the third step of Table 1 suggests the farm (forestry) sector purchases 26% (76%) and 74% (24%) of its output from farm and forestry sectors, respectively.

3.4. Input-Cost Visibility

To calculate input-cost visibility, we require both the composition of input shares for the production of output (the $SUPPSHARE$ matrix in section *3.3*) and price indices published for a supplier sector i in month s.

For each supplier sector i as of month s, the published price indices consist of both "survived indices," whose publications had not been discontinued by the end of our observation period (May, 2018), and "discontinued indices," whose publications had been discontinued by May 2018. To address the survivorship bias, we include both survived and discontinued price indices to calculate the number of monthly publications, as long as they were published during the time that input-cost visibility is a concern. Figure 1 shows the total number of two types of indices across all sectors in month s.

In an economy that consists of n granular sectors supplying each granular customer sector j, we calculate input-cost visibility ($VSBY$) for sector j in month s as follows:

$$VSBY_{j,s} = \frac{\sum_{i=1, i \neq j}^{n} \lambda_{j,i,s} \times Publication\%_{i,s}}{\sum_{i=1, i \neq j}^{n} \lambda_{j,i,s}}, \tag{4}$$

where $Publication\%_{i,s}$ is the number of published indices in supplier sector i as a percentage of the maximum number of monthly publications over the sample period. $\lambda_{j,i,s}$ is the percentage of inputs (as total output) that sector j purchases from a supplier sector i. $\lambda_{j,i,s}$ is an element in the ith row and jth column of the $SUPPSHARE$ matrix.

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In equation (4), we exclude sector j's own $\lambda_{j,j,s}$ and also j's publication status. The periodical introduction, or discontinuation, of j's own product prices might be correlated with how the sector is doing overall, which in turn correlates with unobservables affecting firm outcomes.[13] Figure 2 plots the time series of input-cost visibility for several 3-digit NAICS sectors. Within each 3-digit sector, we calculate the mean of input-cost visibilities across 6-digit sectors. The figure shows our measure steadily evolved over time during 1997-2003 but experienced a discontinuous jump in January 2004, when the PPI program replaced the SIC codes with the NAICS codes.

3.5. Measures of Information Asymmetry

Following prior literature, we employ the following measures to proxy for information asymmetry: the bid-ask spread, the probability of private information-based trading (*PIN*), and analyst forecast dispersion.

Although the bid-ask spread also measures market liquidity, its magnitude should depend not only on inventory, transaction, and order-processing costs, but, more importantly, also on adverse-selection costs.[14] Indeed, during periods of high information asymmetry, specialists widen spreads to compensate for the cost of trading with informed traders. A portion of the spread arises from information asymmetry, and the spread has been used to capture the impact of information asymmetry existing between informed and uninformed traders in various studies (e.g., Copeland and Gailai, 1983; Glosten and Milgrom, 1985; Krinsky and Lee, 1996; Coller and Yohn, 1997; Leuz and Verrecchia, 2000; Coates, 2007; Wittenberg-Moerman, 2008; Bharath et al., 2009).

PIN is a firm-level estimate of the probability that an observed trade originates from privately informed investor.[15] The measure is developed by Easley et al. (2002) from a

[13]Our main results are not materially altered if we include $\lambda_{j,j,s}$ and j's publication status to calculate input-cost visibility. We also include the customer sector's publication status as a control variable (see section *4.2*).

[14]Our untabulated statistics suggest the results are not materially altered if we control for standard measures of liquidity.

[15]The PIN data only include NYSE stocks, which allows the measures to be consistent with those used in existing studies. NASDAQ, for example, is a multiple-dealer market, and its multiple trades based on the same order could affect the recorded number of buys and sells and hence, PIN estimates.

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microstructure model in which order imbalances reflect active trading of informed investors. Specifically, *PIN* is computed as a fraction of orders that arises from informed investors relative to the overall order flow. Lai et al. (2014) validate the quality of *PIN* estimates as good measures of information asymmetry by showing that *PIN* estimates are positively associated with the bid-ask spreads.[16]

Analyst forecast dispersion, which is computed as the dispersion of analysts' earnings per share (EPS) forecasts, is used extensively in the literature (e.g., Diether et al., 2002) to capture the information environment within which the firm operates. In particular, the dispersion of forecasts directly measures the variance of outsiders' view on firms' future profits. Following Johnson (2004), we transform the forecast-dispersion measure into the percentile-rank form.

4. Empirical Results

This section presents our main results. Section *4.1* describes our test sample. Sections *4.2* and *4.3* present panel-regression results and robustness checks, respectively. Section *4.4* presents our results using an IV strategy.

4.1. Sample

We focus on S&P 1500 constituent firms that capture approximately 90% of the available stock market capitalization in the US.[17] For two reasons, we use the sample period from July 1997 through June 2013. First, the NAICS system was first established in 1997 by the BEA.[18] Because both PPIs and price-inflexibility measures are prepared in accordance with the NAICS system, we start the sample in 1997. By doing so, we avoid inconsistent

[16]Our untabulated statistics suggest the results are robust to measures alternative to the PIN model (e.g., Duarte and Young, 2009; Odders-White and Ready, 2008; Duarte et al., 2020).

[17]The S&P 1500 includes all stocks in the S&P 500, S&P 400 (mid-cap stocks), and S&P 600 (small-cap stocks). Consistent with prior literature, the verification of our proposed mechanism among representative firms, if any, has important implications for the transmission of monetary policy (Bernanke and Kuttner, 2005; Gorodnichenko and Weber, 2016).

[18]To convert SIC into NAICS for years before 1997, the BEA relied heavily on concordances developed in 1997. Such a single-year static concordance becomes increasingly unreliable in early years before 1997 as the true relationship between NAICS and SIC changes over time.

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conversion from SIC into NAICS in early years.[19] Second, more importnat data on output-price inflexibility are based on microdata underlying the PPI from 2002 to 2012. Also, our 1997, 2002, and 2007 IO tables correspond to the periods of 1997–2001, 2002–2006, and 2007–2011. To minimize measurement errors arising from using data in 2011 to proxy for post-2012 data, we choose to end the sample in July 2013, which corresponds to the end of year 2012 in Fama and French (1992).

Panel A of Table 2 presents descriptive statistics of variables used in our baseline analysis. *Inflex* is the FPA multiplied by -1. The average *Inflex* is -0.182, suggesting an average sample firm keeps prices constant for 11.5 months.[20] An average firm also has 43.2% of its input costs disclosed by the BLS.

4.2. Baseline Results

We perform weighted least squares (WLS) regressions with firm assets as the weight for the following reasons. First, the BLS samples establishments based on the value of shipments. We assign higher weight to larger firms within the same industry to mitigate potential effects of measurement errors from using industry-level data. Second, our sample is not a random sample. Weights are necessary to adjust the sample to represent the entire population of Compustat firms. Third, weighted regressions can correct for heteroskedastic error terms.[21]

Specifically, we estimate the following panel-regression model:

$$\begin{aligned} Y_{k,t} = \alpha + \beta \times \mathit{Inflex}_j + \gamma \times \mathit{Inflex}_j \times \mathit{VSBY}_{j,t-1} + \delta \times \mathit{VSBY}_{j,t-1} \\ + X'_{k,t-1} \times \theta + \eta_t + \eta_k + \epsilon_{k,t}, \end{aligned} \tag{5}$$

where $Y_{k,t}$ is the empirical proxy for information asymmetry for the period staring from July of year t to June of year t+1. j indexes the 6-digit NAICS sector. $\mathit{VSBY}_{j,t-1}$ is measured

[19]See Yuskavage (2007) for an introduction on how the BEA converted historical industry time-series data from SIC to NAICS.

[20]We use $-1/\log$(1-adjustment frequency) to calculate implied duration.

[21]See Cameron and Triverdi (2008, 2010) and Solon et al. (2015) for more details about weighted regressions.

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according to equation (4) as of year t-1.[22] $X_{k,t-1}$ is a set of control variables, including firm size, book-to-market ratio, intangibility, long-term debt, cash flows, price-to-cost margin, the Herfindahl-Hirschman Index (HHI) measuring market concentration (e.g., Hoberg and Phillips, 2010; Gu, 2016), and the number of analysts following the firm. In addition, we also control for customer sector j's own publication status — a dummy variable indicating whether j's own prices are published — to exclude the possibility that the decision by BLS to publish j correlates with our outcome variables. η_t indicates year-fixed effects, and η_k indicates industry- or firm-fixed effects. Industry is classified by 4-digit SIC codes. We cluster standard errors at the 6-digit NAICS level.

Table 3 presents the panel-regression results. Consistent with our conjecture, output-price inflexibility is positively associated with all empirical measures of information frictions, if we hold input-cost visibility at zero. As columns (1), (4), and (7) show, holding $VSBY$ at zero, a one-standard-deviation increase in *Inflex* is associated with an increase in the bid-ask spread, PIN, and forecast dispersion of 0.4, 0.7, and 4.3 percentage points, respectively. These magnitudes correspond to increases of 12%, 7.4%, and 10% of their sample means, respectively.

Moreover, the estimated coefficients on the interaction term *Inflex* $\times$ $VSBY$ are negative and statistically significant at the 5% level in all specifications, suggesting public disclosures of input-cost data mainly affect inflexible-price firms. As columns (1), (4), and (7) show, for fully inflexible-price firms, a one-standard-deviation increase in input-cost visibility reduces the bid-ask spread, PIN, and dispersion by 0.4, 1.85, and 4.8 percentage points — approximately 12.2%, 19.7%, and 11.3% of the corresponding sample means. However, for fully flexible-price firms, a one-standard-deviation increase in input-cost visibility is associated with an increase in the bid-ask spread, PIN, and forecast dispersion of 0.4, 1.1, and

[22] We lag publication-related variables because the first-published data for a particular month, as well as recalculated indexes (final numbers) for the indices published four months earlier, are available the following month of reference, usually during the second full week. For example, on August 14, 2013, the BLS released the first-published PPIs for July 2013 and final indices for March 2013.

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11 percentage points, respectively, and these magnitudes correspond to increases of 12.1%, 11.7%, and 25.9% of their corresponding sample means.[23]

4.3. Robustness

4.3.1. Wage Share

Our measure of input-cost visibility does not cover labor costs, because we assume an input-cost shock does not include the change in wages, for at least two reasons. First, wages are much stickier than the prices of intermediate goods.[24] Second, compared with costs of input materials, wages are more difficult to manipulate. For this reason, the BLS publication of wage data contains less information incremental to labor expenses disclosed by firms on income statements. However, labor is an import input, and as a result, excluding labor costs in the visibility measure might introduce upward or downward bias to our test results.

To alleviate this concern, we check whether our main results in Table 3 hold in industries with a low wage share, which is computed as the ratio of the customer sector's compensation of employees to total output. Table A.1 reports our baseline results in the subsample in which the wage share is below the 50th percentile (25%) of its sample distribution. As the table shows, both the statistical and economic significance for the estimated coefficients on the interaction term "$Inflex \times VSBY$" are larger after we exclude sectors with high wage shares. Therefore, excluding labor costs in the visibility measure biases downward our baseline results in Table 3.

4.3.2. Time-Varying Input Shares under Coarser BEA Industry Classifications

For each five-year period, the detailed IO accounts use data in 1997, 2002, 2007, and 2012 to forward file IO structures at the level of 6-digit NAICS sectors (see Badertscher et al., 2013). By employing static data at the granular level, we minimize measurement errors in

[23]To illustrate the importance of visibility for inflexible-price firms, we calibrate the above economic magnitudes relative to firm size. Holding price inflexibility at the average level, a one-standard-deviation increase in the logarithm of market capitalization reduces the three outcome variables by 0.3, 1.7, and 4.7 percentage points, respectively.

[24]Wages follow an autoregressive process whereby the wage growth is related to the marginal product of labor (Gertler and Trigari, 2009; Shimer, 2010; Favilukis and Lin, 2016a).

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estimating a customer sector's input share. However, we also recognize the possibility that an econometrician, by doing the above, might encounter another measurement error due to the possibility that input shares vary over years. We therefore use summary-level annual updates to measure less granular IO shares that are surveyed and reported by the BEA on a yearly basis.

Specifically, we employ the use and make tables by 71 BEA industries.[25] We calculate input-cost visibility for a customer sector at the level of a coarser sector by simulating an economy that consists of 71 BEA sectors (indexed by m) supplying 71 coarser BEA customer sectors (indexed by h). Our untabulated statistics suggest auto-correlations of newly constructed input shares with lag 1, 2, 3, 4, and 5 are, respectively, 0.99, 0.99, 0.98, 0.98, and 0.97, suggesting a highly persistent feature of a customer sector's input composition, which alleviates the concern that input shares significantly change over time. In Table A.2, we re-estimate our baseline model in equation (5) using the broader-industry-level visibility for input costs. As the table shows, our baseline results still hold.

4.3.3. Fundamental Volatility

One concern is that output-price inflexibility captures firms' fundamental volatility, and fundamental volatility might explain the effect of output-price inflexibility on information frictions. We alleviate this concern by including proxies for fundamental volatility, firm-fixed effects, and a variety of industry-by-year fixed effects in our regression model. In Panels A and B of Table A.3, we show our baseline results still hold after controlling for the volatility of operating income à la Gorodnichenko and Weber (2016) and the volatility of realized total stock returns ($RetVol$), respectively.[26]

[25]For data sources, please refer to https://www.bea.gov/industry/input-output-accounts-data.

[26]We calculate the firm's volatility of operating income using the change in profitability between the previous four quarters and quarters running from $t+H$ to $t+H+3$:

$$Funda\ Vol = \left(\frac{\frac{1}{4}\sum_{s=t+1}^{t+4} OI_{ks} - \frac{1}{4}\sum_{s=t-4}^{t-1} OI_{ks}}{AT_{kt-1}}\right)^2 \times 100,$$

where OI is the quarterly operating income before depreciation, AT is total assets, and H can be interpreted as the horizon of the response.

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4.4. BLS Conversion of SIC into NAICS

To test our proposed mechanism, we have shown that input-cost visibility weakens the effect of output-price inflexibility on information asymmetry. However, our input-cost visibility measure might be correlated with unobservables that reflect firms' fundamentals. To address this issue, we exploit an exogenous shock to input-cost visibility, which is caused by BLS's conversion from the 1987 SIC system to the NAICS system. Specifically, we construct an instrument for the input-cost visibility measure.

4.4.1. Background

In January 2004, the PPI program switched its basis for industry classification from the 1987 SIC system to the NAICS system. This profound reform was made in response to increasing criticism about the inability of the SIC system to handle rapid changes in the US economy. Developments in information services, new forms of health care, an expansion in the service sector, and the advent of high-tech manufacturing are examples of industrial changes that could not be studied under SIC.

Three major dimensions in which NAICS improves upon SIC make our instrument especially appealing. First, NAICS provides more complete coverage of new and emerging *supplier* sectors at different granularities. These new and emerging industries include semiconductor and related device manufacturing, cellular and other wireless telecommunications, and internet publishing and broadcasting. Second, NAICS groups establishments into industries on the basis of their production function, whereas SIC categorizes economic activities in a mixture of ways. The unified approach creates more homogeneous categories that are better suited for economic analysis. Establishments using similar raw-material inputs, similar capital equipment, and similar labor are classified under the same industry. The third advantage of NAICS relative to SIC is that NAICS is not only used by the US but also by Canada and Mexico. The conversion makes NAICS a consistent tool for measuring and comparing the economies within the North American Free Trade Agreement.[27]

[27]See Walker and Murphy (2001) for more institutional details.

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For price indices prior to 2004, the BLS reorganizes them under the NAICS according to the rule as follows. The PPI treats the SIC-to-NAICS comparison as continuous if 80% or more of the weight of the SIC-based index comprises at least 80% of the weight of the NAICS-based index. All SIC-based index series that have passed this test are published under the NAICS structure using the index base date and price-index history established by the SIC-based index.

Figure 4 shows our input-cost visibility measure, on average, experienced a discontinuous and sizable jump after the exogenous event, but substantial cross-section variation may remain concerning the magnitude of the jump.

4.4.2. Instrument

To construct an instrument for input-cost visibility, we follow the spirit of Azar et al. (2018) and Giannetti and Saidi (2019) to take advantage of the cross-supplier-sector variation in the implied change in BLS publication coverage. To illustrate this cross-sector heterogeneity, Panels A and B of Table A.8 provide a comparison of publication expansion under the new NAICS system after the BLS abandoned the SIC system. For petroleum and coal products manufacturing, the SIC-based indices are fully comparable to the NAICS-based ones. For textile mills, by contrast, only 48% of SIC-based indices are comparable to the NAICS-based ones, triggering a release of the remaining 52% of NAICS-based indices after January 2004.

We calculate the change in input-cost visibility before and after January 2004 for each consumer sector j as follows:

$$\Delta VSBY_j^{2004} = VSBY_{j,200401} - VSBY_{j,200212}, \tag{6}$$

where $VSBY_{j,200212}$ and $VSBY_{j,200401}$ are input-cost visibility measured as of December 2002 and January 2004, respectively. We use December 2002 as the benchmark to mitigate the concern that sectors experiencing the greatest coverage expansion was associated with a one-

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time period of relatively low coverage before January 2004.[28] Figure 3 plots the distribution of the change in input-cost visibility before and after January 2004 across sample units.

To minimize measurement errors, we then transform $\Delta VSBY_j^{2004}$ into a percentile rank-form: $\Delta Rank_j^{2004}$.[29] Following prior literature (e.g., Azar et al., 2018; Giannetti and Saidi, 2019), we construct the IV as follows:

$$IV = \Delta Rank_j^{2004} \times Post, \tag{7}$$

where $Post$ is an indicator variable that equals 1 if year t is after the event year, and 0 otherwise. Because the data for January 2004 under the NAICS system were eventually published on March 18, 2004, and because we follow Fama and French (1992) to time lag firm characteristics, we define an event year as the year spanning from July 2004 until June 2005.

Our instrument satisfies the exclusion restriction. The expansion of BLS's publication coverage into new supplier sectors is unlikely to correlate with customer-sector-level unobservables determining information asymmetries among outsiders. The cross-customer-sector variation of changes in input-cost visibility based on equation (6) before and after January 2004 is mostly driven by the cross-supplier-sector variation in the matching quality between the NAICS and SIC systems, weighted by input shares that remain constant around the exogenous event. Thus, the variation in $\Delta VSBY_j^{2004}$ across customer sectors is solely driven by the variation in the release of new price indices from supplier sectors. Arguing such a variation correlates with customer-sector-level economic conditions is difficult.

[28]Our IV estimation results hold if we use input-cost visibility of November 2013 ($VSBY_{j,200311}$) as the benchmark. Table A.4 reports these results. Because the BLS lags four months to public finalized data, we avoid using December 2003 to mitigate the concern that publication coverage for December 2003 might have already reflected the expansion program.

[29]The benefit of a continuous treatment version of the instrument is that it makes use of more variations; the relative costs of using it is to encounter measurement errors. For robustness, we also construct the instrument with the continuous treatment of $\Delta VSBY_j^{2004}$ and our IV estimation results still hold. Tables A.5 and A.6 report these results.

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4.4.3. IV Estimation

Panel A of Table 4 reports the estimates of the first-stage regression that includes industry- and year- fixed effects. Panel B reports the estimates of the first-stage regression that includes firm- and year- fixed effects. Specifically, two endogenous variables — *VSBY* and its interaction with price inflexibility (*Inflex* × *VSBY*) — are instrumented by *IV* and *Inflex* × *IV*. The estimates satisfy the relevance condition. That is, *IV* and *Inflex* × *IV* are strongly positively correlated with *VSBY* and *Inflex* × *VSBY*, respectively. The F-statistics from weak identification tests are larger than 10 in all specifications, suggesting our instruments are strong.[30]

Table 5 reports estimates from the second stage of the IV estimation. As the table shows, the IV estimation results are qualitatively similar to our baseline results in Table 3, and the economic magnitude of the estimated coefficients on both *Inflex* and *Inflex* × *VSBY* are reasonably increased. The IV estimation results are also robust when we construct the instrument using the change in input-cost visibility from November 2003 to January 2004 or when we use the summary IO tables with 71 industries to construct the input-cost visibility measure. Tables A.4 and A.7 report these results, respectively.

4.4.4. Dynamic Effects

We then study how our information-asymmetry measures respond to changes in the BLS's publication coverage over time. Specifically, we estimate the dynamic effect as follows:

$$\begin{aligned} Y_{k,t} = \alpha + \sum_{t=-7}^{8} \beta_t \times \mathit{Inflex} \times \Delta \mathit{Rank}_j + \sum_{t=-7}^{8} \gamma_t \times \mathit{Inflex} + \sum_{t=-7}^{8} \theta_t \times \Delta \mathit{Rank}_j \\ + \kappa \mathit{Inflex} \times \Delta \mathit{Rank}_j + X'_{k,t-1} \times \theta + \eta_t + \eta_k + \epsilon_{k,t}, \end{aligned} \tag{8}$$

where we drop the interactions with 2004, which serves as the base period. Thus, the estimated β coefficients represent the change in the difference between treatment (i.e., firms

[30]Following the recommendation of Jiang (2017), we also estimate the partial R^2 of the excluded IV in explaining the variation in the endogenous variable. Our untabulated statistics show the partial R^2 is about 20%, suggesting the excluded IV well explains the variation in the endogenous variable.

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more exposed to coverage expansion) and control (i.e., firms less exposed to less expansion) groups between 2004 and the given period, and such a change varies across output-price inflexibility.

As Figure 5 shows, whereas the difference between the treatment and control firms with inflexible output-price fluctuates somewhat around zero during the pre-period, the overall trend before 2004 is flat and no pre-trends were discernable. The trend, however, changes one to two years after BLS switched to the NAICS system, and the coefficients are significantly negative for most periods after 2004. Thus, the sign of the effect, based on variation in input-cost visibility generated by the BLS's publication expansion, is consistent with our story. In particular, we do not find an anticipation effect, suggesting the dynamic effects are not driven by changing industrial fundamentals that forced the BLS to adopt new industry classifications.

5. Corroborating Evidence

We now provide additional evidence to support our main intuition that output-price inflexibility suppresses the revelation of firm-value-related information and thereby exacerbates information asymmetry. Specifically, we examine (1) whether security analysts inquire about more cost-related information during conference calls of inflexible-price firms, (2) whether the stock market reacts more strongly to earnings news of inflexible-price firms, and (3) whether managers of inflexible-price firms tend to issue more earnings guidance.

5.1. Analysts' Access to Management

5.1.1. Textual Analysis

The textual content of questions analysts ask during the Q&A session provides a unique setting to gauge the extent to which output-price inflexibility contributes to information frictions between firm insiders and outsiders. We obtain conference-call-transcript data from Thomson Reuters, specifically from the StreetEvents data feed. We collect the complete

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transcripts of all US conference calls for the period from January 2002 to June 2013. We exclude scripts in which the length of the Q&A session is less than 1,000 words.

Following several criteria, we textually extract analyst questions from Q&A sessions of each transcript that are related to the production cost of the hosting company. First, the cost-related-word list includes "cost(s)," "expense(s)," "expenditure(s)," "spend," and "spending." We exclude wording indicating expenses related to capital expenditure, compensation, mergers and acquisitions, and pensions. Second, we require cost-related sentences to be in future tense, because information about historical input-costs, irrespective how noisy it is, has already been disclosed in companies' financial statements. If firms fail to reset product price to cost shocks, the impact of cost shock on profits will persist into the future, and investors cannot costlessly observe such an impact.[31] To check whether the extracted words are indeed related to firms' production costs, we manually read all extracted sentences and questions and make sure they contain references to the cost-related words that we are interested in. Figure 6 lists five examples to better illustrate the output of our textual analysis.

To further provide a visual representation of extracted sentences, we resort to textual-analysis techniques and build on the Latent Dirichlet Allocation (LDA) first developed by Blei et al. (2003). The LDA reduces the dimensionality of linguistic data from words to topics, based on word co-occurrences within a same document. The LDA algorithm analyzes the text of the full universe of sentences of our interest to identify common topics (e.g., D'Acunto et al., 2020; Lopez-Lira, 2020).[32]

Figure 7 illustrates four sample topics. Each graph is a cloud representation of the two crucial elements of each topic — the words that are related enough to constitute a topic, as well as the probabilities attached to each word (font size). For example, consider the topic on the top left. The words with the highest probability of belonging to this topic are "cost," "production," and "development." Other words seem less likely but are still present in some

[31]Our estimates are quantitatively similar if we include cost-related sentences in the simple present tense.

[32]Each topic is a matrix that contains two types of elements — a set of words that the procedure identifies as related to each other in terms of their meaning, as well as a probability attached to each word, which captures the probability that the word is indeed semantically related to the other words within the topic.

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sentences, as is evident from the words "gas," "project," and "future" showing up with lower probabilities.

One important control variable is managers' discussion about costs during the presentation session, which increases the possibility that analysts ask cost-related questions during the Q&A session. We therefore also extract sentences related to managers' discussion about company costs during the presentation session. We follow several criteria similar to how we extract questions asked by analysts.

5.1.2. Empirical Results

Panel B of Table 2 presents descriptive statistics on this test sample. On average, 7.5% of analysts asked cost-related questions during the Q&A session. We then estimate the following regression model:

$$\begin{aligned} Question_{k,n,q} = \alpha + \beta \times \mathit{Inflex}_j + \gamma \times \mathit{Inflex}_j \times VSBY_{j,q-1} + \delta \times VSBY_{j,q-1} \\ + X'_{k,t-1} \times \theta + \eta_q + \eta_k + \epsilon_{k,n,q}, \end{aligned} \tag{9}$$

where $Question_{k,n,q}$ is an indicator that equals 1 if analysts ask at least one question concerning firm k's future production costs during the Q&A session of the nth conference call hosted by the firm in year-quarter q, and 0 otherwise.

Table 6 reports our estimation results. Our estimates suggest analysts are more likely to ask questions concerning input costs if hosting companies are inflexible-price firms, and this likelihood is substantially reduced by input-cost visibility. In column (1), holding input-cost visibility at zero, a one-standard-deviation increase in output-price inflexibility increases the likelihood of analysts inquiring about input costs by 4.6%, and this effect is almost doubled by the IV estimation in column (3). When we exploit within-industry variations in column (1), input-cost visibility does not significantly reduce the likelihood that analysts ask cost-related questions, although the sign of the coefficient on the interaction term is negative. However, when we exploit within-firm variations in column (2), the coefficient on the interaction term *Inflex* $\times$ *VSBY* turns out to be statistically and economically negative.

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This effect increases by more than 50% under the IV estimation in columns (3) and (4). In column (3), for example, a one-standard-deviation increase in input-cost visibility reduces the positive impact of price inflexibility on the outcome variable by 21%.

Existing studies find managers discriminate among analysts during the Q&A section based on how favorably the analyst views the firm (Mayew, 2008; Cohen et al., 2019). If the management team of inflexible-price firms dislikes disclosing cost-related information and, as a result, intentionally solicits analysts to do favors by not asking cost-related questions, the coefficients in Table 6 are underestimated.

5.2. Stock-Market Pricing of Earnings News

We then investigate how investors of inflexible-price and flexible-price firms react to announcements of earnings news. If output-price inflexibility suppresses the revelation of firm-value related information and exacerbates information asymmetry, we would expect that inflexible-price firms' initial market reaction should be higher per unit of the surprise component for earnings. Specifically, we estimate the following regression model:

$$\begin{aligned} CAR_{k,q} = \alpha + \beta \times \mathit{Inflex}_j + \gamma \times \mathit{Inflex}_j \times SUE_{k,q} + \delta \times SUE_{k,q} + \\ X'_{k,t-1} \times \theta + + \eta_q + \eta_k + \epsilon_{k,q}. \end{aligned} \tag{10}$$

For the dependent variable, we consider cumulative abnormal returns over the window [-1, +1] days relative to the date in which firm k announces quarter q earnings. SUE measures the earnings surprise as the I/B/E/S actual earnings per share (EPS) minus I/B/E/S median forecast in the 90-day period before the earnings announcement date, scaled by price per share at quarter q. SUE is transformed into the percentile rank form.

Panel A of Table 7 reports the estimates on the effect of output-price inflexibility on the initial market reaction to earnings news. We find robust evidence that holding the size of earnings surprise constant, inflexible-price firms are associated with stronger stock-market reactions over a tight-window surrounding earnings announcements. A one-standard-

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deviation increase in output-price inflexibility increases the earnings-response coefficient by about 15%, and the results are fairly robust across all specifications.

An alternative interpretation of our findings is that investors of inflexible-price firms might have lower transaction costs for price discovery (e.g., Ng et al., 2008; Zhang et al., 2013). To test this hypothesis, we consider the implication for long-term price drift. If inflexible-price firms' higher initial market reaction suggests more severe information asymmetries of inflexible-price firms, we should not observe different long-term price drifts across firms with differential inflexibility. By contrast, the transaction-cost effect on the initial market reaction will be corrected through the price movement driven by the gradual incorporation of the earnings-surprise information by capital-market participants. It therefore predicts that transaction costs will be positively correlated with the size of drift. Panel B of Table 7 shows output-price inflexibility fails to explain the cross-firm variation in the size of post-earnings-announcement drift, thereby rejecting the transaction-cost hypothesis.

5.3. Managerial Earnings Guidance and Universal Demand Law

Given more severe information asymmetry of inflexible-price firms, we now ask whether managers of these firms have more incentives to issue earnings guidance. However, a mere positive correlation between output-price inflexibility and the frequency of earnings guidance could be explained by many unobservables jointly determining product pricing and managerial behaviors. To address endogeneity, we exploit the staggered adoption of UD law to show inflexible-price firms issued more earnings guidance after an exogenous reduction in managerial-perceived litigation risk on corporate disclosure.

5.3.1. Background

A shareholder derivative suit is a lawsuit brought by a shareholder on behalf of a corporation against insiders (e.g., executive offers or directors) of the corporation for their alleged wrongdoings. Typical examples of such allegations include violations of US Generally Accepted Accounting Principles (GAAP), hiding material information, inappropriate management be-

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havior in transactions, inappropriate engagement in related party transactions, and insider trading. In most jurisdictions, a shareholder must first make a demand on the corporate board to bring legal action against the wrongdoers. Generally, the directors rarely want to approve the demand, because, if approved, the majority of them are named as defendants in derivative lawsuits. If the board of directors disapprove the demand, a judge typically follows the board's decision and dismisses the lawsuit. The universal demand requirement imposes a significant hurdle on derivative litigation by always requiring board approval, barring irreparable harm (Jost, 1994).

To lower the hurdle in filing a derivative lawsuit, and to mitigate directors' conflict of interest arising from the demand requirement, many US states follow the "demand futility" doctrine — a specific type of civil lawsuit in which a company's board decisions are challenged. In the context of derivative lawsuits, such a doctrine allows shareholders to file a lawsuit without obtaining the directors' approval. To do so, shareholders need to prove the majority of directors cannot impartially judge the necessity of initiating a derivative lawsuit. Plaintiffs, however, often abuse the demand futility doctrine to focus on unqualifying directors to take actions rather than to demonstrate insiders' wrongdoings that breach fiduciary duties (Swanson, 1993).

Between 1989 and 2005, 23 US states eliminated the demand futility doctrine with a UD law. The demand requirement is determined by the firms' state of incorporation. By re-validating demand requirements, the adoption of UD laws again raised up the procedural hurdle by granting controls of derivative lawsuits back to directors.

Bourveau et al. (2018) document that firms issued more earnings forecasts after staggered adoption of UD law.[33] Huang et al. (2020) confirm that Bourveau et al.'s findings

[33]Donelson et al. (2020) employ data from Advisen's Loss database and show UD laws are not significantly related to derivative litigation frequency over the period of 1996 – 2015. The authors also find Bourveau et al.'s (2018) results only hold if headquarter state-year fixed effects are added. We reconcile our findings with Donelson et al.'s (2020) as follows. First, similar to Boone et al. (2021) and others, our analysis merely requires that managers perceive a reduction in litigation risk and change their behavior accordingly, regardless of realized lawsuit frequency. Second, we estimate differential treatments to exploit cross-firms variation in price inflexibility. Even if a treatment effect averaged across firms within a state does not exist, as argued by Donelson et al. (2020), our estimates speak to a within-state variation of such a treatment effect. Third, our research design allows us to control for time trends within each state of incorporation, which, by design, cannot be controlled in Bourveau et al. (2018) and Huang et al. (2020).

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are driven by lower perceived litigation risks inducing managers to issue more long-horizon forecasts (e.g., annual earnings forecasts), which resolves earnings uncertainty ex ante but ex post might turn out to be overly optimistic. The adoption of UD law provides a natural experiment to test our story. Specifically, firms that are subject to greater information frictions, and hence will benefit more from disclosure, should issue more earnings guidance in response to a lower possibility of litigation on corporate disclosure.

5.3.2. Empirical Results

We employ the following difference-in-differences design to compare the likelihoods and frequencies of guidance before and after the adoption of UD laws between inflexible- and flexible-price firms:

$$\begin{aligned} \mathit{Ln(\#Forecasts)}_{k,t} = \alpha + \beta \times \mathit{Inflex}_j + \gamma \times \mathit{Inflex}_j \times \mathit{Post\ UD}_{i,t} + \delta \times \mathit{Post\ UD}_{i,t} \\ + X'_{k,t-1} \times \theta + \eta_t + \eta_k + \epsilon_{k,t}, \end{aligned} \tag{11}$$

where $Y_{k,t}$ is measured as the natural logarithm of 1 plus number of management earnings forecasts issued in year t, and 0 otherwise. *Post UD* is an indicator equal to 1 for all years after a state passed a UD law, and 0 otherwise. Table A.9 presents descriptive statistics on firm-year observations in states that passed the law during the period of 1989-2005.

Table 8 reports the estimates of effect of the adoption of UD law on managers' tendency to forecast own companies' EPS. Columns (1)-(2) report the estimation results on the logarithm of the number of earnings guidance. On average, managers issued more guidance after the adoption of UD law. However, the effect of UD law is more pronounced for inflexible-price firms. The interaction term *Inflex* $\times$ *Post UD* is not only statistically positive but also economically sizable, and the estimates are robust to the inclusion of state-incorporation-year effects to account for time trends at the state level. In columns (3)-(6), we separately calculate the number of annual and quarterly earnings forecasts. We confirm that managers of inflexible-price firms issued more annual forecasts relative to quarterly forecasts after the adoption of UD law.

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A necessary condition for identification is the parallel-trends assumption, which states that the evolution of forecasting behaviors of managers for sticky-price firms (treated) and flexible-price firms (controlled) would have followed common trends before the adoption of UD law. Panel A in Figure 8 plots the estimated β and 95% confidence intervals from the following specification:

$$Y_{k,t} = \alpha + \sum_{8}^{10} \beta_t \times \mathit{Inflex} + X'_{k,t-1} \times \theta + \eta_t + \eta_k + \epsilon_{k,t}, \tag{12}$$

where we drop the interactions with event year 0, which serves as the base period. We fail to detect any systemic, pre-adoption difference in earnings guidance across firms. However, inflexible-price firms more frequently issued forecasts starting from the first and second years after adoption, and the difference between the two groups gradually builds up over time. Interestingly, Panels B and C show the pattern in Panel A is entirely driven by annual earnings forecasts, which have longer horizons.

6. Conclusion

Firms differ in the frequency with which they adjust output prices. Firms' inflexibility in adjusting output prices suppresses the revelation of the impact of economic shocks on firm profits and thereby exacerbates information asymmetry. We show that a novel form of public information about firms' input costs is particularly valuable to outsiders of inflexible-price firms.

We close with a discussion of caveats, policy implications, and possible avenues for future research. Our paper is silent on why publicly available statistics do not mitigate flexible-price firms' information asymmetry. One possible explanation is that by directly observing price changes, investors have already had a good picture of flexible firms' cost shocks and profits. As such, officially released macro data might provide little incremental information content to decision-makers holding stakes in flexible-price firms. Another possible explanation is that the detrimental effects of public information can dominate in the sense that already-

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better-informed investors, because of coordination motives, abandon their private signals to overweight public signals sent by the government's statistic agency.

Our findings point to an interaction between nominal price rigidities and information frictions in the transmission of monetary policy. Because price rigidity is key to monetary policy having its real effects, our proposed empirical environment is relevant to the design of public policy. Two recent papers document novel and important evidence suggesting monetary-policy shocks affect the real economy through firm-level information quality. Ozdagli (2018) uses the Enron accounting scandal and Arthur Andersen's demise as a large exogenous shock to document that stock prices of Anderson's clients, which were subject to greater information frictions, have a weaker reaction to monetary policy. Armstrong et al. (2019) propose that the quality of firms' accounting reports plays a role in transmitting monetary policy by affecting information asymmetries between firm insiders and outsiders. To further assess the importance of this issue, an examination of the joint effect of output-price inflexibility and information frictions in the transmission of monetary policy to the real economy would be interesting.

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Fig. 1. **BLS Publication: Survived vs. Discontinued Price Indices**

The dashed-blue series represents all price indices that were published at the time and still "survived" by the time we gathered the data. The dark-red series represents all indices that were being published at the time, but were discontinued by the time we gathered the data.

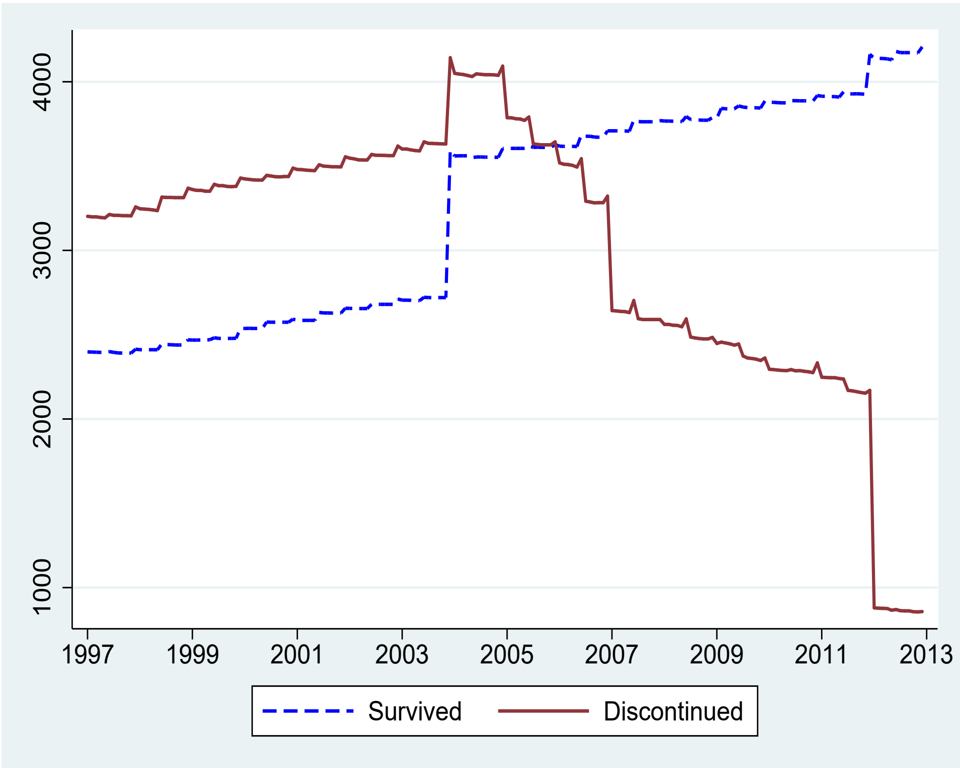

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Fig. 2. **Input-Cost Visibility over Time**

For each 3-digit NAICS sector, the dashed-blue series represents the mean of input-cost visibilities (measured as in equation (4)) across 6-digit NAICS sectors. For each 3-digit NAICS sector, the dark-red series represents the mean of input-cost visibilities (measured as in equation (4)) across 6-digit NAICS sectors.

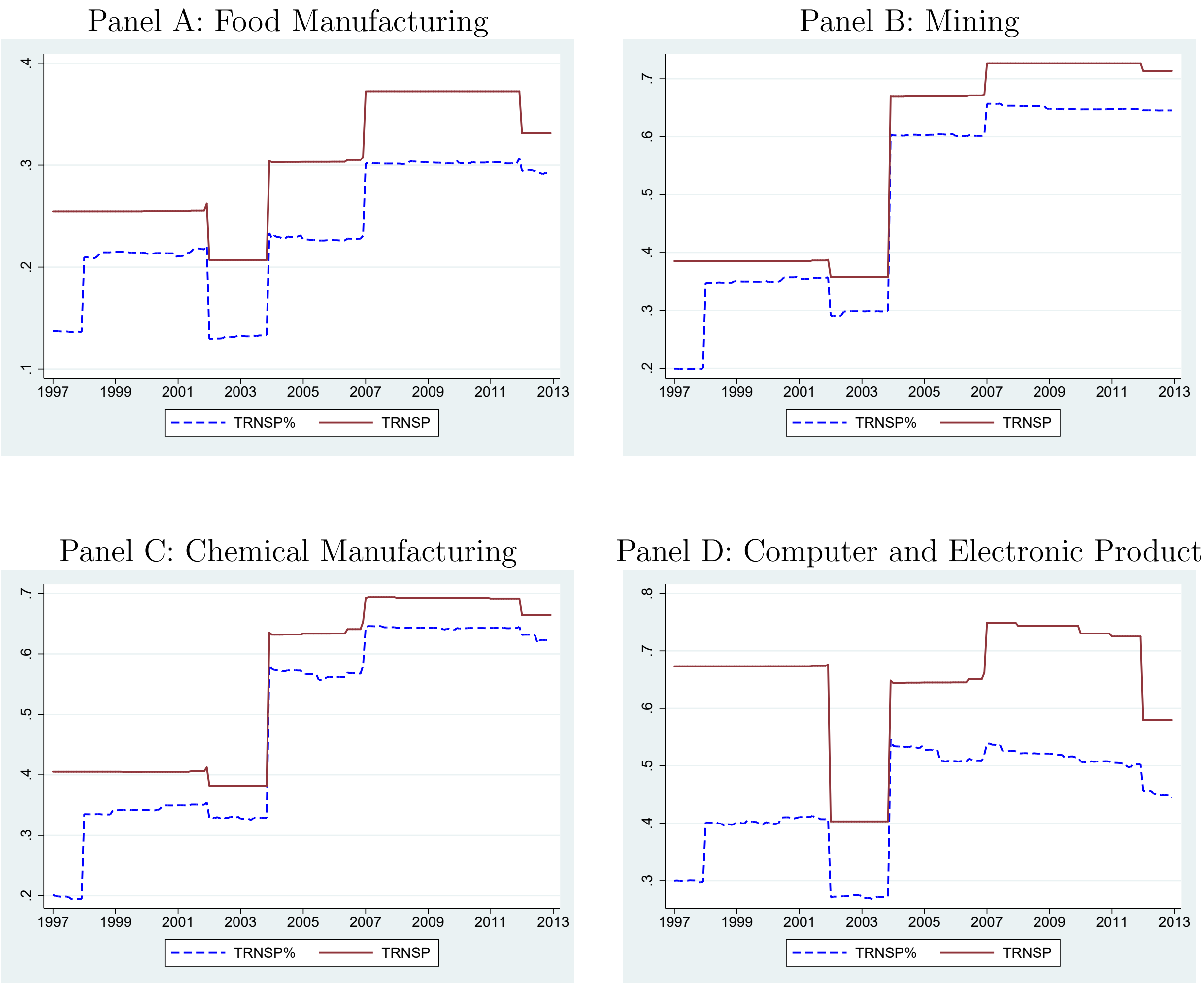

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Fig. 3. **Cross-Sectional Distribution of Changes in Input-Cost Visibility**

This figure plots the distribution of the implied change in input-cost visibility ($VSBY$) from December 2002 to January 2004 across 6-digit NAICS sectors across firm-year observations in the regression sample. The sample period is from July 1997 to June 2013. Input-cost visibility is measured as in equation (4). The change of input-cost visibility from December 2002 to January 2004 is measured as in equation (6).

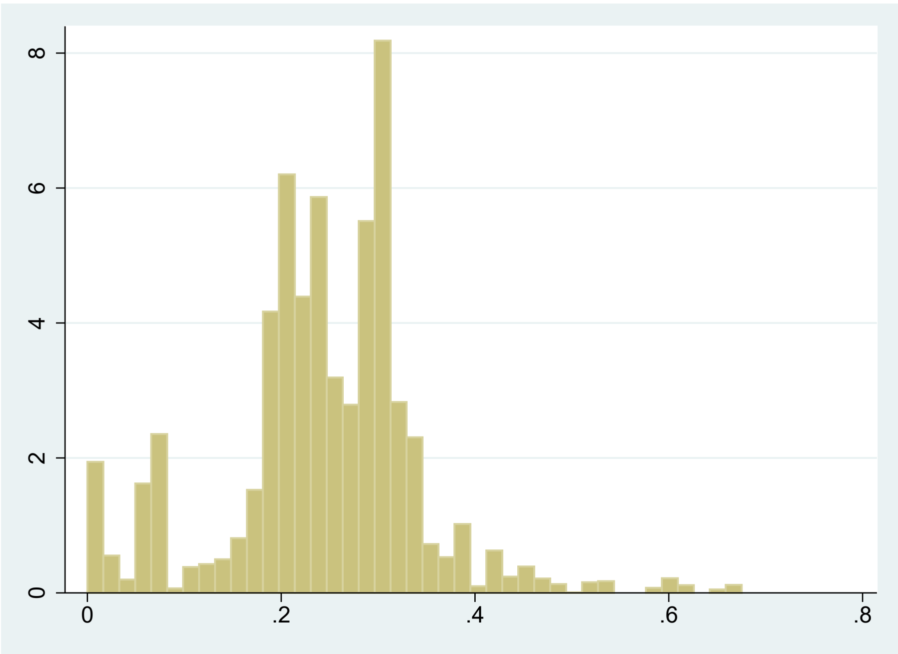

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Fig. 4. **Input-Cost Visibility around January 2004**

The figure plots the estimates of β_t and the 95% confidence intervals. The sample period is from July 1997 to June 2013. The sample is restricted to S&P 1500 firms. Utilities and financial sectors are excluded. Year 0 represents the event year, during which BLS switched from SIC to NAICS. The excluded event year is 0. We estimate the following model, and observations are weighted by firm assets:

$$VSBY_{k,t} = \alpha + \sum_{t=-7}^{8} \beta_t + X'_{k,t-1} \times \theta + \eta_t + \eta_k + \epsilon_{k,t},$$

Standard errors are clustered at the level of 6-digit NAICS sectors.

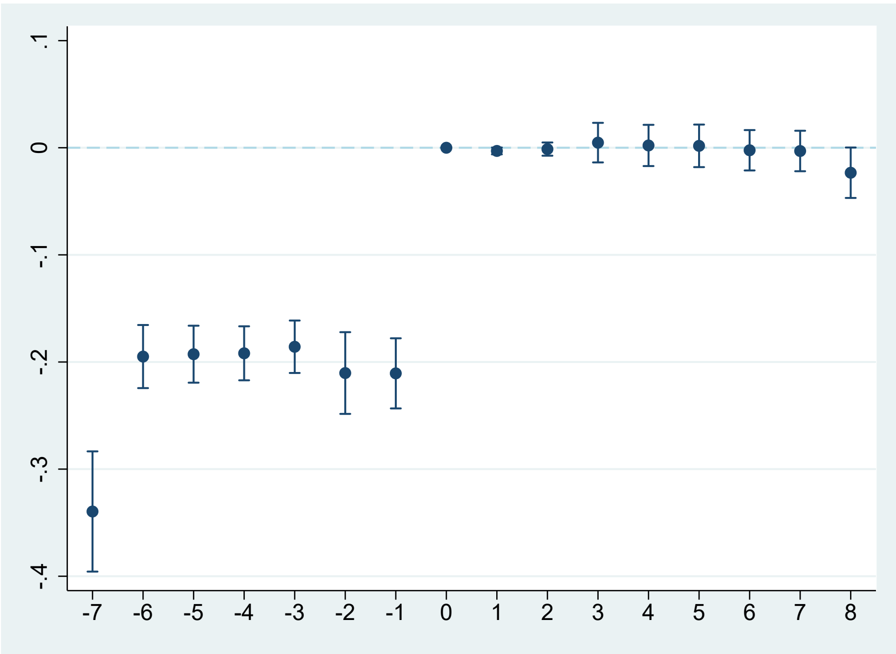

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Fig. 5. **Information Frictions around January 2004**

The figure plots the estimates of β_t and the 95% confidence intervals. The sample period is from July 1997 to June 2013. The sample is restricted to S&P 1500 firms. Utilities and financial sectors are excluded. Year 0 represents the event year, during which BLS switched from SIC to NAICS. Year 0 is excluded. We estimate the following model, and observations are weighted by firm assets:

$$Y_{k,t} = \alpha + \sum_{t=-7}^{8} \beta_t \times \times \mathit{Inflex} \times \Delta \mathit{Rank}_j + \sum_{t=-7}^{8} \gamma_t \times \mathit{Inflex} + \sum_{t=-7}^{8} \theta_t \times \Delta \mathit{Rank}_j + \kappa \times \mathit{Inflex} \times \Delta \mathit{Rank}_j$$
$$+ X'_{k,t-1} \times \theta + \eta_k + \eta_t + \epsilon_{k,t}.$$

For each firm k in year t, $Y_{k,t}$ is measured as the average of daily bid-ask spreads (*Bid-Ask Sprd*) in Panel A, the *PIN* computed by Easley et al. (2002) in Panel B, and the percentile-rank-form transformed standard deviation of two-year-ahead analyst EPS forecasts divided by the absolute value of actual EPS (*Dispersion*) in Panel C. *Inflex* is the frequency of price adjustment (*FPA*) multiplied by -1. $\Delta \mathit{Rank}_j$ is the percentile-rank-transformed difference between input-cost visibilities in January 2004 and December 2002 ($\Delta \mathit{VSBY}_j$). Standard errors are clustered at the level of 6-digit NAICS sectors.

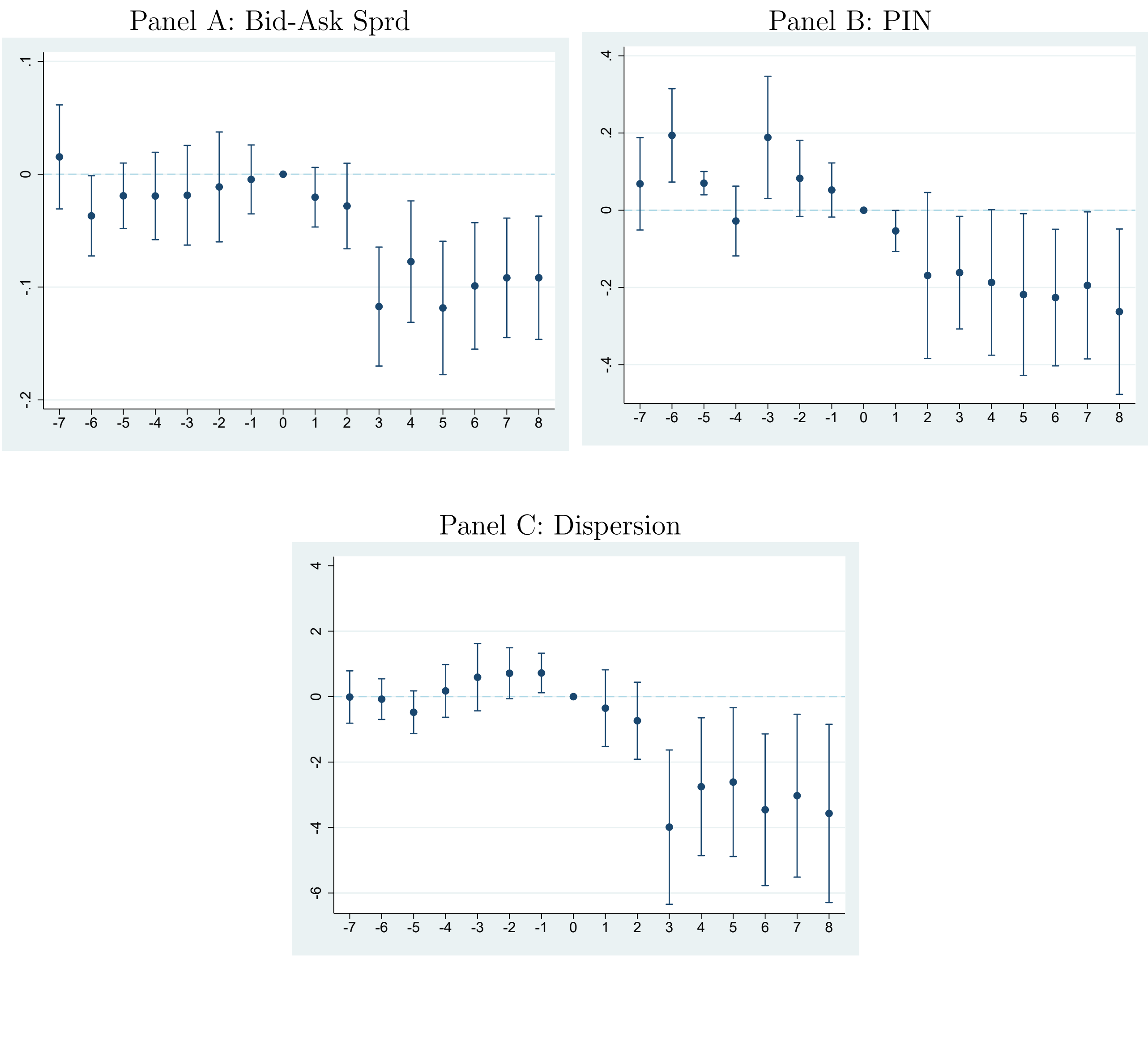

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Fig. 6. **Examples of Extracted Sentences**

This figure uses five examples to illustrate sentences that we extract from conference calls. These five sentences are related to inquiries by analysts (outsiders) about companies' production costs during the Q&A session.

1. Okay, and to the extent that, and knowing there's lack of predictability, can you give us some sense on some of your raw material input costs, whether it's nickel, titanium, et cetera, and say, in expectation in the next three to 12 months? — Carpenter Technology Corp, Oct 28, 2008

2. This 3% cost of goods per case estimate, or guidance that we are seeing today, if you could break that down a little bit, maybe looking more so at raw materials and packaging costs? — Pepsi Co Inc, Aug 4, 2009

3. Can you tell us a little bit about how you expect your material costs to trend, as you ramp up, and when you think they can come down once you have the volume behind you to help you had that 25% gross margin target? — Tesla Motors Inc, Aug 3, 2019

4. In the fourth quarter your direct store expenses after three pretty good quarters in a row, performance was – absolute dollars were up a little bit over 3%, I know in the release you said healthcare and depreciation, but any reason why one quarter would stand out a little bit worse than the prior few quarters? — Whole Foods Market Inc, Nov 04, 2004

5. Would it be reasonable, then, to assume that your production costs will fall by something more towards the 20% to 30% by the time the whole process is worked through? — Occidental Petroleum Corp, Apr 23, 2009

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Fig. 7. **Examples of LDA Topics**

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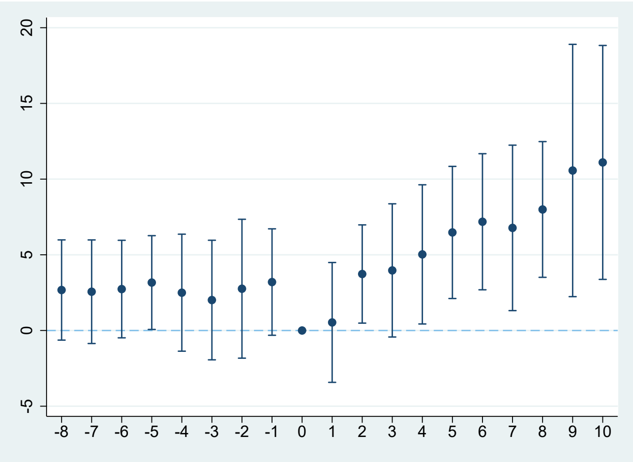
Fig. 8. **Earnings Guidance around the Adoption of Universal Demand Laws**

The figure plots the estimates of β and the 95% confidence intervals. The sample period is from July 1997 to June 2013. The sample is restricted to S&P 1500 firms. Utilities and financial sectors are excluded. Year 0 represents the event year, during which the state in which firm k is incorporated passed the UD law. Year 0 is excluded. We estimate the following model, and observations are weighted by firm assets:

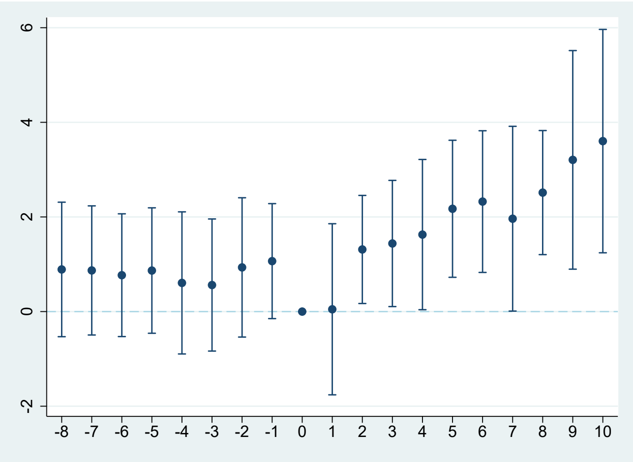
$$Y_{k,t} = \alpha + \sum_{t=-8}^{10} \beta_t \times \mathit{Inflex} + \eta_t + \eta_k + \epsilon_{k,t}.$$

For each firm k in year t, $Y_{k,t}$ is measured as the natural logarithm of 1 plus the number of all earnings guidance issued in year t (Panel A), the natural logarithm of 1 plus the number of all annual earnings guidance issued in year t (Panel B), and the natural logarithm of 1 plus the number of all quarterly earnings guidance issued in year t (Panel C), respectively. Standard errors are clustered at the level of the firm's state of incorporation.

Panel A: All EPS Guidance



Panel B: Annual EPS Guidance



Panel C: Quarterly EPS Guidance

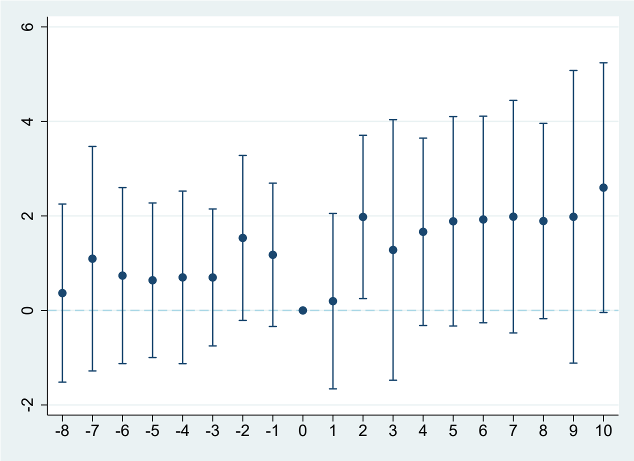


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Table 1: **A Two-Sector Example**

This table presents a two-sector example to illustrate the three-step procedure to calculate the *SUPPSHARE* matrix as in equation (3). The hypothetical economy consists of two sectors — farm and forestry — that not only supply to each other but also purchase from each other. Each sector earns zero profits from production.

	Make Table				Use Table	
Sector/Commodity	Farm	Forestry	Output	Commodity/Sector	Farm	Forestry
Farm	900	100	1,000	Farm	200	800
Forestry	100	900	1,000	Forestry	800	200
				Input	1,000	1,000

Step 1: Market Share		
Sector/Commodity	Farm	Forestry
Farm	90%	10%
Forestry	10%	90%

Step 2: Revenue Share		
Commodity/Sector	Farm	Forestry
Farm	260	740
Forestry	740	260

Step 3: Supplier Share		
Sector/Sector	Farm	Forestry
Farm	26%	74%
Forestry	74%	26%
	100%	100%

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Table 2: **Descriptive Statistics**

Panel A reports descriptive statistics based on the Compustat-CRSP matched sample. The sample period is from July 1997 to June 2013. The sample is restricted to S&P 1500 firms. Utilities and financial sectors are excluded. *Inflex* is the frequency of price adjustment (FPA) for each 6-digit NAICS sector, multiplied by -1. *VSBY* is the measure of input-cost visibility for each 6-digit NAICS sector (see equations (4) for detailed descriptions). *SelfDisclosure* is a dummy variable indicating whether customer sector j's own output prices are published by the BLS. *Bid-Ask Sprd* is the average of daily bid-ask spreads calculated from July of year t through June of t+1. *PIN* is the probability of informed trading developed by Easley et al. (2002). *Raw Dispersion* is the standard deviations of two-year-ahead analyst EPS forecasts scaled by stock price as of June of calendar year t. *Dispersion* is the percentile-rank-form-transferred *Raw Dispersion*. *RetVol* is the standard deviation of the raw daily returns calculated from July of year t through June of t+1. *RetVol* is annualized. *Assets* (in millions) is the sum of total liabilities and equity. *Size* is the natural logarithm of the total market capitalization (in thousands) in June of year t. *BM* is the book equity for the fiscal year ending in calendar year t-1 over the market equity as of December t-1. *Lev* is debt maturing in more than two years to total assets. *HHI* is the Herfindahl-Hirschman Index based on sales of Compustat firms. *PCM* is the price-to-cost margin. *Intangibility* is intangible assets over total assets. Tangible assets are defined as total assets minus the sum of net property, plant, and equipment; cash and short-term investments; total receivables; and total inventories. *CF* is the sum of income before extraordinary items and depreciation and amortization over total assets. *Ln(#Analysts)* is the natural logarithm of number of analysts covering the firm.

Panel B reports descriptive statistics based on the conference-call sample. The sample period is from January 2002 to June 2013. The sample unit is at the conference-call transcript level. We exclude call scripts in which the length of the Q&A session (measured by number of words) is less than 1,000 words. *Question* is an indicator that equals 1 if analysts participating in the conference call ask at least one question related to the hosting company's production cost in the Q&A session, and 0 otherwise. *Presentation* is an indicator that equals 1 if managers participating the conference call quantitatively forecast future production costs in the presentation session, and 0 otherwise.

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	Mean	Std	P1	P10	P25	P50	P75	P90	P99	N
	Panel A. Compustat-CRSP Matched Sample									
Inflex	-0.182	0.113	-0.694	-0.318	-0.212	-0.162	-0.108	-0.088	-0.062	12,241
VSBY	0.432	0.161	0.065	0.218	0.318	0.437	0.537	0.639	0.791	12,241
SelfDisclosure	0.673	0.469	0.000	0.000	0.000	1.000	1.000	1.000	1.000	12,241
Bid Ask Sprd	0.033	0.016	0.011	0.017	0.022	0.030	0.040	0.054	0.087	12,178
PIN	0.094	0.049	0.018	0.033	0.055	0.091	0.125	0.158	0.224	6,188
Raw Dispersion	0.009	0.061	0.000	0.001	0.001	0.002	0.006	0.014	0.083	10,539
Dispersion	0.424	0.270	0.010	0.073	0.189	0.400	0.639	0.817	0.966	10,539
RetVol	0.445	0.218	0.154	0.227	0.297	0.393	0.537	0.731	1.190	11,639
Assets	5,021	15,714	81	220	457	1,133	3,330	10,435	65,937	12,241
Size	14.396	1.526	11.504	12.656	13.307	14.188	15.301	16.442	18.669	12,241
BM	0.491	0.388	0.042	0.147	0.251	0.407	0.621	0.916	1.829	12,241
Lev	0.388	0.172	0.061	0.155	0.256	0.392	0.506	0.611	0.798	12,241
HHI	0.084	0.066	0.031	0.038	0.042	0.060	0.102	0.158	0.360	12,241
PCM	0.412	0.287	0.041	0.180	0.272	0.397	0.554	0.706	0.917	12,241
Intangibility	0.326	0.188	0.028	0.095	0.175	0.300	0.456	0.589	0.804	12,241
CF	0.146	0.095	-0.133	0.057	0.099	0.143	0.194	0.252	0.395	12,241
Ln(#Analysts)	1.785	0.962	0.000	0.000	1.099	1.946	2.485	2.944	3.466	12,241
	Panel B. Conference Call Sample									
Question	0.074	0.262	0.000	0.000	0.000	0.000	0.000	0.000	1.000	28,399
Presentation	0.248	0.432	0.000	0.000	0.000	0.000	0.000	1.000	1.000	28,399
Inflex	-0.182	0.106	-0.694	-0.302	-0.202	-0.167	-0.113	-0.088	-0.062	28,399
VSBY	0.488	0.141	0.096	0.304	0.415	0.495	0.569	0.655	0.912	28,399
SelfDisclosure	0.779	0.415	0.000	0.000	1.000	1.000	1.000	1.000	1.000	28,399
Assets	12,115	25,405	142	440	1,074	3,229	11,121	32,728	121,271	28,399
Size	8.396	1.672	5.097	6.296	7.134	8.291	9.550	10.780	12.203	28,399
BM	0.446	0.281	0.009	0.164	0.250	0.386	0.580	0.799	1.456	28,399
Lev	0.381	0.169	0.060	0.159	0.262	0.384	0.479	0.585	0.838	28,399
HHI	0.061	0.039	0.026	0.030	0.034	0.051	0.071	0.116	0.215	28,399
PCM	0.458	0.226	0.054	0.193	0.296	0.436	0.608	0.788	0.906	28,399
Intangibility	0.381	0.195	0.038	0.125	0.228	0.366	0.522	0.646	0.826	28,399
CF	0.143	0.086	-0.089	0.062	0.099	0.138	0.187	0.240	0.374	28,399
Ln(#Analysts)	2.762	0.770	0.000	1.792	2.303	2.890	3.296	3.611	3.989	28,399

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Table 3: **Inflexible Prices, Cost Visibility, and Information Asymmetry**

This table reports our estimation results for the effect of inflexibility and cost visibility on information asymmetry proxies. The sample period is from July 1997 to June 2013. The sample is restricted to S&P 1500 firms. Utilities and financial sectors are excluded. We estimate the following model, and observations are weighted by firm assets:

$$Y_{k,t} = \alpha + \beta \times \mathit{Inflex}_j + \gamma \times \mathit{Inflex}_j \times VSBY_{j,t-1} + \delta \times VSBY_{j,t-1} + X'_{k,t-1} \times \theta + \eta_t + \eta_k + \epsilon_{k,t}.$$

For each firm k in year t, $Y_{k,t}$ is measured as the average of daily bid-ask spreads (*Bid-Ask Sprd*), the *PIN* computed by Easley et al. (2002), and *Dispersion*, the percentile rank form of *Raw Dispersion*, which is computed as the standard deviation of two-year-ahead analyst EPS forecasts divided by the absolute value of actual EPS. Inflex_j is the frequency of price adjustment (*FPA*) for each 6-digit NAICS customer sector j, multiplied by -1. $VSBY_{j,t-1}$ is the input-cost visibility for each 6-digit NAICS customer sector j. *Industry* is a set of dummies indicating 4-digit SIC industries. See Table 2 for detailed descriptions of all variables. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the level of 6-digit NAICS sectors.

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	Bid-Ask Sprd			PIN			Dispersion		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Inflex	0.033***	0.028***		0.065***	0.055***		0.384*	0.472**	
	(0.006)	(0.005)		(0.019)	(0.017)		(0.220)	(0.192)	
Inflex × VSBY	-0.049***	-0.053***	-0.050***	-0.185***	-0.086***	-0.103**	-0.972***	-0.928***	-0.747***
	(0.010)	(0.009)	(0.010)	(0.033)	(0.026)	(0.047)	(0.247)	(0.153)	(0.178)
VSBY	-0.025***	-0.010	-0.009	-0.116***	-0.042***	-0.031*	-0.304***	-0.287***	-0.297***
	(0.005)	(0.007)	(0.006)	(0.012)	(0.015)	(0.017)	(0.099)	(0.087)	(0.087)
Self-Disclosure	-0.002	0.000	0.000	-0.005**	-0.002	0.002	-0.003	-0.015	-0.014
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.022)	(0.011)	(0.010)
Size	-0.002***	-0.002***	-0.003***	-0.011***	-0.012***	-0.015***	-0.031***	-0.040***	-0.064***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.009)	(0.009)	(0.015)
BM	0.005***	0.004**	0.002**	-0.004	-0.001	-0.000	0.127***	0.123***	0.007
	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.015)	(0.020)	(0.017)
Lev	-0.004	-0.001	-0.002	0.008	-0.008	0.001	0.035	0.109**	0.032
	(0.003)	(0.003)	(0.003)	(0.007)	(0.006)	(0.010)	(0.063)	(0.052)	(0.056)
HHI	-0.003	0.002	0.007	-0.005	0.020	0.104	-0.126	0.482	0.566
	(0.004)	(0.010)	(0.010)	(0.009)	(0.037)	(0.084)	(0.248)	(0.410)	(0.414)
PCM	0.002	-0.002	-0.012***	-0.002	0.012	0.005	-0.182***	-0.070	0.046
	(0.002)	(0.002)	(0.004)	(0.007)	(0.008)	(0.014)	(0.059)	(0.060)	(0.041)
Intangibility	-0.016***	-0.006***	-0.004	-0.009	0.015*	0.011	-0.385***	-0.087	0.059
	(0.003)	(0.002)	(0.003)	(0.007)	(0.008)	(0.013)	(0.053)	(0.056)	(0.062)
CF	-0.024***	-0.017***	-0.006	0.027**	0.009	0.008	-0.476***	-0.168	0.092
	(0.007)	(0.006)	(0.005)	(0.011)	(0.021)	(0.019)	(0.149)	(0.158)	(0.123)
Ln(#Analysts)	0.002***	0.001***	0.001***	-0.007***	-0.004***	-0.001	0.077***	0.081***	0.086***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.025)	(0.015)	(0.017)
Constant	0.084***	0.066***	0.072***	0.309***	0.275***	0.287***	1.071***	0.876***	1.169***
	(0.006)	(0.005)	(0.015)	(0.016)	(0.020)	(0.035)	(0.155)	(0.133)	(0.278)
Year FE		X	X		X	X		X	X
Industry FE		X			X			X	
Firm FE			X			X			X
N	12,178	12,178	12,178	6,188	6,188	6,188	9,845	9,845	9,845
Adjusted R^2	0.31	0.60	0.67	0.49	0.67	0.75	0.35	0.56	0.66

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Table 4: **IV Estimation: First Stage**

This table reports the first-stage results for instrumental variable (IV) estimation. The sample period is from July 1997 to June 2013. The sample is restricted to S&P 1500 firms. Utilities and financial sectors are excluded. We estimate the following model, and observations are weighted by firm assets:

$$Y_{k,t} = \alpha + \beta \times \mathit{Inflex}_j + \gamma \times \mathit{Inflex}_j \times \mathit{VSBY}_{j,t-1} + \delta \times \mathit{VSBY}_{j,t-1} + X'_{k,t-1} \times \theta + \eta_t + \eta_k + \epsilon_{k,t}.$$

For each firm k in year t, $Y_{k,t}$ is measured as the average of daily bid-ask spreads (*Bid-Ask Sprd*), the *PIN* computed by Easley et al. (2002), and *Dispersion*, the percentile rank form of *Raw Dispersion*, which is computed as the standard deviation of two-year-ahead analyst EPS forecasts divided by the absolute value of actual EPS. Inflex_j is the frequency of price adjustment (*FPA*) for each 6-digit NAICS customer sector j, multiplied by -1. $\mathit{VSBY}_{j,t-1}$ is the input-cost visibility for each 6-digit NAICS customer sector j. $\mathit{VSBY}_{k,t}$ and $\mathit{Inflex}_j \times \mathit{VSBY}_{k,t}$ are instrumented by IV and $\mathit{Inflex}_j \times \mathit{IV}$, respectively. IV is $\mathit{Post} \times \Delta \mathit{Rank}_j$. $\Delta \mathit{Rank}_j$ is the percentile-rank-transformed difference between input-cost visibilities in January 2004 and December 2002 ($\Delta\, \mathit{VSBY}_j^{2004}$). *Post* is an indicator that equals 1 if year t is after 2004, and 0 otherwise. Panel A includes a set of industry (4-digit SIC)- and year-fixed effects. Panel B includes a set of firm- and year-fixed effects. See Table 2 for detailed descriptions of control variables. *Time* is a full set of dummies indicating years. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the level of 6-digit NAICS sectors.

Panel A: Industry- and Year-Fixed Effects

	Bid-Ask Sprd		PIN		Dispersion	
	(1)	(2)	(3)	(4)	(5)	(6)
IV	0.185***	0.079***	0.217***	0.078***	0.210***	0.066***
	(0.046)	(0.022)	(0.049)	(0.022)	(0.046)	(0.020)
IV × Inflex	-0.366***	0.543***	-0.346***	0.548***	-0.353***	0.529***
	(0.077)	(0.039)	(0.079)	(0.041)	(0.080)	(0.037)
Controls	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X
N	12,092	12,092	6,131	6,131	9,772	9,772
F-stat	17.51	106.58	15.75	91.62	17.29	111.31

Panel B: Firm- and Year-Fixed Effects

	Bid-Ask Sprd		PIN		Dispersion	
	(1)	(2)	(3)	(4)	(5)	(6)
IV	0.242***	0.040**	0.262***	0.037*	0.255***	0.036*
	(0.046)	(0.020)	(0.049)	(0.020)	(0.046)	(0.019)
IV × Inflex	-0.322***	0.461***	-0.298***	0.458***	-0.315***	0.460***
	(0.080)	(0.033)	(0.085)	(0.032)	(0.084)	(0.032)
Controls	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X
N	11,943	11,943	6,085	6,085	9,611	9,611
F-stat	18.39	108.94	16.46	104.33	18.84	112.37

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Table 5: **IV Estimation: Second Stage**

This table reports the second-stage results for instrument variable (IV) estimation. The sample period is from July 1997 to June 2013. The sample is restricted to S&P 1500 firms. Utilities and financial sectors are excluded. We estimate the following model, and observations are weighted by firm assets:

$$Y_{k,t} = \alpha + \beta \times \mathit{Inflex}_j + \gamma \times \mathit{Inflex}_j \times VSBY_{j,t-1} + \delta \times VSBY_{j,t-1} + X'_{k,t-1} \times \theta + \eta_t + \eta_k + \epsilon_{k,t}.$$

For each firm k in year t, $Y_{k,t}$ is measured as the average of daily bid-ask spreads (*Bid-Ask Sprd*), the *PIN* computed by Easley et al. (2002), and *Dispersion*, the percentile rank form of *Raw Dispersion*, which is computed as the standard deviation of two-year-ahead analyst EPS forecasts divided by the absolute value of actual EPS. Inflex_j is the frequency of price adjustment (*FPA*) for each 6-digit NAICS customer sector j, multiplied by -1. $VSBY_{j,t-1}$ is the input-cost visibility for each 6-digit NAICS customer sector j. $VSBY_{k,t}$ and $\mathit{Inflex}_j \times VSBY_{k,t}$ are instrumented by IV and $\mathit{Inflex}_j \times IV$, respectively. IV is $\mathit{Post} \times \Delta \mathit{Rank}_j$. $\Delta \mathit{Rank}_j$ is the percentile-rank-transformed difference between input-cost visibilities in January 2004 and December 2002 ($\Delta\, VSBY_j^{2004}$). *Post* is an indicator that equals 1 if year t is after 2004, and 0 otherwise. See Table 2 for detailed descriptions of control variables. *Industry* is a full set of dummies indicating 4-digit SIC industries. *Time* is a full set of dummies indicating years. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the level of 6-digit NAICS sectors.

	Bid-Ask Sprd		PIN		Dispersion	
	(1)	(2)	(3)	(4)	(5)	(6)
Inflex	0.039***		0.081***		0.492*	
	(0.013)		(0.028)		(0.279)	
Inflex × VSBY	-0.089***	-0.104***	-0.114***	-0.142***	-1.018***	-0.749***
	(0.018)	(0.022)	(0.037)	(0.053)	(0.235)	(0.193)
VSBY	0.004	-0.004	-0.115***	-0.124***	-0.722***	-0.529***
	(0.015)	(0.013)	(0.033)	(0.033)	(0.209)	(0.169)
Controls	X	X	X	X	X	X
Time FE	X	X	X	X	X	X
Industry FE	X		X		X	
Firm FE		X		X		X
N	12,092	11,943	6,131	6,085	9,772	96,11

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Table 6: **Inflexible Prices, Cost Visibility, and Analysts: Conference Calls**

This table reports our estimation results for the effect of inflexibility and cost visibility on questions asked by security analysts in conference calls. The sample period is from January 2002 to June 2013. The sample is restricted to S&P 1500 firms. Utilities and financial sectors are excluded. We estimate the following model, and observations are weighted by firm assets:

$$Question_{k,n,q} = \alpha + \beta \times Inflex_j \times VSBY_{j,q-1} + \gamma \times VSBY_{j,q-1} + X'_{k,t-1} \times \theta + \eta_q + \eta_k + \epsilon_{k,n,q},$$

where $Question_{k,n,q}$ is an indicator that equals 1 if analysts ask at least one question about the hosting company's production costs during the Q&A session in the nth conference call hosted by firm k in year-quarter q, and 0 otherwise. In columns (1)-(2), we perform linear probability regression; in columns (3)-(4), we perform IV estimation, where $VSBY_{k,t}$ and $Inflex_j \times VSBY_{k,t}$ are instrumented by IV and $Inflex_j \times IV$, respectively. IV is $Post \times \Delta Rank_j$. $\Delta Rank_j$ is the percentile-rank-transformed difference between input-cost visibilities in January 2004 and December 2002 ($\Delta VSBY_j$). We exclude call scripts in which the Q&A session is less than 1,000 words. *Industry* is a full set of dummies indicating 4-digit SIC industries. *Time* is a full set of dummies indicating year-quarters. See Table 2 for detailed descriptions of control variables. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the level of 6-digit NAICS sectors.

	WLS		IV Estimation	
	(1)	(2)	(3)	(4)
Inflex	0.432**		0.838**	
	(0.199)		(0.404)	
Inflex × VSBY	-0.394	-0.825***	-1.244***	-1.350***
	(0.342)	(0.264)	(0.449)	(0.381)
VSBY	-0.121	-0.178***	0.034	-0.038
	(0.078)	(0.060)	(0.157)	(0.105)
Self-Disclosure	-0.009	-0.017*	0.003	-0.010
	(0.012)	(0.009)	(0.013)	(0.011)
Presentation	0.040***	0.039***	0.040***	0.039***
	(0.008)	(0.007)	(0.008)	(0.007)
Size	0.004	0.007	0.004	0.006
	(0.004)	(0.011)	(0.004)	(0.012)
BM	0.026	0.010	0.031*	0.017
	(0.018)	(0.019)	(0.018)	(0.023)
Lev	0.032	-0.009	0.033	0.004
	(0.035)	(0.055)	(0.037)	(0.053)
HHI	0.785*	0.869**	0.986**	0.987***
	(0.464)	(0.424)	(0.402)	(0.379)
PCM	0.033	-0.008	0.034	-0.004
	(0.034)	(0.043)	(0.038)	(0.047)
Intangibility	0.015	-0.001	0.006	-0.013
	(0.021)	(0.045)	(0.030)	(0.053)
CF	-0.065	-0.097	-0.048	-0.096
	(0.087)	(0.098)	(0.098)	(0.104)
Ln(# Analysts)	0.003	-0.001	0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.005)
Constant	0.029	-0.064		
	(0.109)	(0.160)		
Time FE	X	X	X	X
Industry FE	X		X	
Firm FE		X		X
N	28,399	28,399	28,393	28,386
Adjusted R^2	0.07	0.07		

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Table 7: **Stock-Market Reaction to Earnings Surprises**

This table reports our estimation results for stock market reactions to earnings surprises. The sample period is from July 1997 to June 2013. The sample is restricted to S&P 1500 firms. Utilities and financial sectors are excluded. We estimate the following model, and observations are weighted by firm assets:

$$CAR_{k,q} = \alpha + \beta \times \mathit{Inflex}_j + \gamma \times \mathit{Inflex}_j \times SUE_{k,q} + \delta \times SUE_{k,q} + X'_{k,t-1} \times \theta + \eta_q + \eta_k + \epsilon_{k,q}.$$

In Panel A, *CAR* is the cumulative abnormal return in the window of (-1, +1) around the date in which firm k's earnings in year-quarter q is announced. In Panel B, *CAR* is the cumulative abnormal return calculated from the second day after the announcement of firm k's earnings in year-quarter q until the last day prior to the announcement of earnings in year-quarter q+1. Daily abnormal returns are adjusted by six Size-BM portfolios. *SUE* is the I/B/E/S actual EPS minus I/B/E/S median forecast in the 90-day period before the earnings announcement date, scaled by price per share at quarter q. *SUE* is transformed into percentile rank form. *Industry* is a full set of dummies indicating 4-digit SIC industries. *Time* is a full set of dummies indicating year-quarters. See Table 2 for detailed descriptions of control variables. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the level of 6-digit NAICS sectors.

Panel A. Earnings Response Coefficient

	(1)	(2)	(3)	(4)
Inflex	-0.040***	-0.056***		
	(0.012)	(0.016)		
Inflex × SUE	0.084***	0.094***	0.102***	0.097***
	(0.018)	(0.019)	(0.020)	(0.020)
SUE	0.103***	0.111***	0.115***	0.221***
	(0.009)	(0.009)	(0.010)	(0.049)
Controls	X	X	X	X
Controls × SUE				X
Time FE		X	X	X
Industry FE		X		
Firm FE			X	X
N	49,122	49,122	49,122	49,122
Adjusted R^2	0.09	0.11	0.11	0.11

Panel B. Post-Earnings Announcement Drift

	(1)	(2)	(3)	(4)
Inflex	-0.020	-0.068		
	(0.020)	(0.046)		
Inflex × SUE	0.023	0.018	0.008	-0.014
	(0.033)	(0.036)	(0.033)	(0.046)
SUE	0.019	0.011	-0.004	-0.082
	(0.014)	(0.014)	(0.014)	(0.087)
Controls	X	X	X	X
Controls × SUE				X
Time FE		X	X	X
Industry FE		X		
Firm FE			X	X
N	49,122	49,122	49,122	49,122
Adjusted R^2	0.00	0.05	0.05	0.05

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Table 8: **Universal Demand Law and Managerial Earnings Guidance**

This table reports our estimating results for the effect of the adoption of UD law on managerial earnings guidance. The sample period is from July 1997 to July 2013. The sample is restricted to S&P 1500 firms. Utilities and financial sectors are excluded. We estimate the following model, and observations are weighted by firm assets:

$$Y_{k,t} = \alpha + \beta \times \mathit{Inflex}_j + \gamma \times \mathit{Inflex}_j \times \mathit{Post\ UD}_{i,t} + \delta \times \mathit{Post\ UD}_{i,t} + X'_{k,t-1} \times \theta + \eta_t + \eta_k + \epsilon_{k,t}.$$

For each firm k in year t, $Y_{k,t}$ is measured as the natural logarithm of 1 plus the number of management earnings forecasts (columns (1)-(2)), the natural logarithm of 1 plus the number of annual earnings forecasts (columns (3)-(4)), and 1 plus the number of quarterly management earnings forecasts (columns (5)-(6)), respectively. Inflex_j is the frequency of price adjustment (*FPA*) for each 6-digit NAICS customer sector j, multiplied by -1. *Post UD* is an indicator that equals 1 for all years after a state in which firm k is incorporated passed a UD law, and 0 otherwise. *State* is the firm's state of incorporation. *Time* is a full set of dummies indicating years. See Table 2 for detailed descriptions of control variables. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the level of a firm's state of incorporation.

	Ln(#Forecasts)		Ln(#Annual)		Ln(#Quarterly)	
	(1)	(2)	(3)	(4)	(5)	(6)
Inflex × Post UD	1.436**	5.151***	1.324**	3.889***	0.927*	3.712***
	(0.580)	(1.065)	(0.570)	(1.168)	(0.494)	(1.430)
Post UD	0.327**		0.436**		0.077	
	(0.146)		(0.211)		(0.144)	
Size	0.138**	0.131***	0.089*	0.089*	0.112***	0.102***
	(0.059)	(0.050)	(0.049)	(0.046)	(0.039)	(0.032)
BM	-0.102**	-0.100**	-0.115**	-0.096**	-0.010	-0.028
	(0.042)	(0.042)	(0.047)	(0.045)	(0.026)	(0.021)
CF	0.185	0.596	0.353	0.769*	0.040	0.274
	(0.601)	(0.487)	(0.550)	(0.439)	(0.362)	(0.322)
PCM	-0.426	-0.549	-0.517	-0.615	-0.069	-0.161
	(0.420)	(0.443)	(0.425)	(0.462)	(0.145)	(0.116)
Lev	0.005	0.243	0.050	0.316	-0.069	0.020
	(0.258)	(0.207)	(0.244)	(0.204)	(0.172)	(0.123)
HHI	0.185	0.010	0.589	0.311	1.194*	1.240**
	(1.179)	(1.066)	(1.216)	(1.117)	(0.647)	(0.572)
Intangibility	0.077	0.074	0.085	0.115	-0.026	-0.035
	(0.346)	(0.349)	(0.336)	(0.318)	(0.195)	(0.188)
Ln(#Analysts)	0.114***	0.102***	0.080***	0.062**	0.067***	0.070***
	(0.029)	(0.030)	(0.027)	(0.027)	(0.016)	(0.017)
Constant	-1.325	-1.151	-0.755	-0.743	-1.504**	-1.285**
	(0.981)	(0.816)	(0.765)	(0.706)	(0.694)	(0.592)
Firm FE	X	X	X	X	X	X
Time FE	X		X		X	
State × Time FE		X		X		X
N	16,165	16,165	16,165	16,165	16,165	16,165
Adjusted R^2	0.69	0.71	0.68	0.71	0.62	0.66

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Online Appendix:
Price Rigidities and the Value of Public Information

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Table A.1: **Inflexible Prices, Cost Visibility, and Information Asymmetry: Low Wage Share**

This table reports our estimation results for the effect of inflexibility and cost visibility on information-asymmetry proxies with a restricted sample. The sample is restricted to customer sectors in which the "compensation of employees" as a percentage of the customer sector's total output is below 25%. The sample period is from July 1997 to June 2013. The sample is restricted to S&P 1500 firms. Utilities and financial sectors are excluded. We estimate the following model, and observations are weighted by firm assets:

$$Y_{k,t} = \alpha + \beta \times \mathit{Inflex}_j + \gamma \times \mathit{Inflex}_j \times \mathit{VSBY}_{j,t-1} + \delta \times \mathit{VSBY}_{j,t-1} + X'_{k,t-1} \times \theta + \eta_t + \eta_k + \epsilon_{k,t}.$$

For each firm k in year t, $Y_{k,t}$ is measured as the average of daily bid-ask spreads (*Bid-Ask Sprd*), the *PIN* computed by Easley et al. (2002), and *Dispersion*, the percentile rank form of *Raw Dispersion*, which is computed as the standard deviation of two-year-ahead analyst EPS forecasts divided by the absolute value of actual EPS. Inflex_j is the frequency of price adjustment (*FPA*) for each 6-digit NAICS customer sector j, multiplied by -1. $\mathit{VSBY}_{j,t-1}$ is the input-cost visibility for each 6-digit NAICS customer sector j. *Industry* is a set of dummies indicating the 4-digit SIC industries. See Table 2 for detailed descriptions of all variables. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the level of 6-digit NAICS sectors.

	Bid-Ask Sprd			PIN			Dispersion		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Inflex	0.040***	0.047***		0.083***	0.049*		0.723***	0.704**	
	(0.010)	(0.010)		(0.021)	(0.026)		(0.267)	(0.281)	
Inflex × VSBY	-0.054***	-0.101***	-0.114***	-0.199***	-0.080*	-0.025	-1.372***	-1.563***	-1.319***
	(0.016)	(0.018)	(0.019)	(0.042)	(0.044)	(0.046)	(0.322)	(0.358)	(0.403)
VSBY	-0.027***	-0.025***	-0.028***	-0.109***	-0.039**	-0.014	-0.424***	-0.396***	-0.418***
	(0.008)	(0.008)	(0.008)	(0.017)	(0.018)	(0.020)	(0.126)	(0.108)	(0.113)
Year FE		X	X		X	X		X	X
Industry FE		X			X			X	
Firm FE			X			X			X
N	5,407	5,407	5,407	3,106	3,106	3,106	4,401	4,401	4,401
Adjusted R^2	0.35	0.66	0.72	0.47	0.66	0.75	0.44	0.64	0.72

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Table A.2: **Inflexible Prices, Cost Visibility, and Information Asymmetry: Coarser BEA Industry Classifications**

This table reports our estimation results for the effect of inflexibility and cost visibility on information-asymmetry proxies when cost visibility is constructed for coarser BEA industry classifications. The sample period is from July 1997 to June 2013. The sample is restricted to S&P 1500 firms. Utilities and financial sectors are excluded. We estimate the following model, and observations are weighted by firm assets:

$$Y_{k,t} = \alpha + \beta \times \mathit{Inflex}_j + \gamma \times \mathit{Inflex}_j \times \mathit{VSBY}_{h,t-1} + \delta \times \mathit{VSBY}_{h,t-1} + X'_{k,t-1} \times \theta + \eta_t + \eta_k + \epsilon_{k,t}.$$

For each firm k in year t, $Y_{k,t}$ is measured as the average of daily bid-ask spreads (*Bid-Ask Sprd*), the *PIN* computed by Easley et al. (2002), and *Dispersion*, the percentile rank form of *Raw Dispersion*, which is computed as the standard deviation of two-year-ahead analyst EPS forecasts divided by the absolute value of actual EPS. Inflex_j is the frequency of price adjustment (*FPA*) for each 6-digit NAICS customer sector j, multiplied by -1. $\mathit{VSBY}_{h,t-1}$ is the input-cost visibility for each coarser BEA industry classification h. See Table 2 for detailed descriptions of all variables. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the level of 6-digit NAICS sectors. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the level of 6-digit NAICS sectors.

	Bid-Ask Sprd	PIN	Dispersion
	(1)	(2)	(3)
Inflex × VSBY	-0.017***	-0.047*	-0.441***
	(0.006)	(0.026)	(0.135)
VSBY	-0.021**	-0.031	-0.107
	(0.009)	(0.028)	(0.123)
Controls	X	X	X
Year FE	X	X	X
Firm FE	X	X	X
N	12,178	6,188	9,845
Adjusted R^2	0.66	0.69	0.65

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Table A.3: **Inflexible Prices, Cost Visibility, and Information Asymmetry: Fundamental Volatility**

This table reports our estimation results for the effect of inflexibility and cost visibility on information-asymmetry proxies when fundamental volatility measures are included as a control. The sample period is from July 1997 to June 2013. The sample is restricted to S&P 1500 firms. Utilities and financial sectors are excluded. We estimate the following model, and observations are weighted by firm assets:

$$Y_{k,t} = \alpha + \beta \times \mathit{Inflex}_j + \gamma \times \mathit{Inflex}_j \times VSBY_{j,t-1} + \delta \times VSBY_{j,t-1} + X'_{k,t-1} \times \theta + \eta_t + \eta_k + \epsilon_{k,t}.$$

For each firm k in year t, $Y_{k,t}$ is measured as the average of daily bid-ask spreads (*Bid-Ask Sprd*), the *PIN* computed by Easley et al. (2002), and *Dispersion*, the percentile rank form of *Raw Dispersion*, which is computed as the standard deviation of two-year-ahead analyst EPS forecasts divided by the absolute value of actual EPS. Inflex_j is the frequency of price adjustment (*FPA*) for each 6-digit NAICS customer sector j, multiplied by -1. $VSBY_{j,t-1}$ is the input-cost visibility for each 6-digit NAICS customer sector j. In Panel A, we add *Funda Vol* and *Inflex* $\times$ *Funda Vol* as additional control variables. We calculate the firm's volatility of operating income using the change in profitability between the previous four quarters and quarters running from $t+H$ to $t+H+3$:

$$\mathit{Funda\ Vol} = \left(\frac{\frac{1}{4}\sum_{s=t+1}^{t+4} OI_{ks} - \frac{1}{4}\sum_{s=t-4}^{t-1} OI_{ks}}{AT_{kt-1}}\right)^2 \times 100,$$

where OI is the quarterly operating income before depreciation, AT is total assets, and H can be interpreted as the horizon of the response. In Panel B, we add *RetVol* and *Inflex* $\times$ *RetVol* as additional control variables. *RetVol* is the annualized standard deviation of the raw daily returns calculated from July of year t through June of t+1. *Industry1*, *Industry2*, and *Industry3* are three sets of dummies indicating the 1-digit SIC industry, Fama-French 48 industry, and Hoberg-Phillips-50 industry, respectively. See Table 2 for detailed descriptions of all variables. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the level of 6-digit NAICS sectors.

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	Bid-Ask Sprd			PIN			Dispersion		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A. Controlling for Fundamental Volatility								
Inflex × VSBY	-0.038***	-0.039***	-0.033**	-0.094**	-0.087*	-0.095***	-0.565***	-0.844***	-0.425**
	(0.010)	(0.013)	(0.013)	(0.036)	(0.048)	(0.032)	(0.213)	(0.207)	(0.196)
VSBY	-0.005	-0.014***	-0.010**	-0.054***	-0.014	-0.029**	-0.230**	-0.248***	-0.209**
	(0.006)	(0.005)	(0.004)	(0.017)	(0.017)	(0.011)	(0.107)	(0.080)	(0.094)
N	10,565	10,565	10,565	5,423	5,423	5,423	9,332	9,332	9,332
Adjusted R^2	0.71	0.79	0.80	0.71	0.76	0.76	0.69	0.74	0.74
	Panel B. Controlling for Return Volatility								
Inflex × VSBY	-0.024***	-0.023**	-0.022*	-0.100***	-0.090*	-0.075**	-0.559***	-0.675***	-0.389**
	(0.008)	(0.010)	(0.012)	(0.033)	(0.052)	(0.037)	(0.212)	(0.170)	(0.198)
VSBY	0.004	-0.007	-0.006	-0.056***	-0.020	-0.013	-0.095	-0.081	-0.186*
	(0.006)	(0.006)	(0.005)	(0.017)	(0.020)	(0.015)	(0.094)	(0.098)	(0.101)
	(0.003)	(0.002)	(0.002)	(0.016)	(0.014)	(0.011)	(0.043)	(0.035)	(0.037)
N	11,578	11,578	11,578	6,028	6,028	6,028	10,538	10,538	10,538
Adjusted R^2	0.77	0.82	0.83	0.70	0.75	0.75	0.69	0.74	0.73
Controls	X	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X	X
Industry1 × Time FE	X			X			X		
Industry2 × Time FE		X			X			X	
Industry3 × Time FE			X			X			X

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Table A.4: **IV Estimation: December, 2003 as Benchmark**

This table reports the first-stage and second-stage results for instrument variable (IV) estimation when December 2013 is used as the benchmark to construct the instrument. The sample period is from July 1997 to June 2013. The sample is restricted to S&P 1500 firms. Utilities and financial sectors are excluded. We estimate the following model, and observations are weighted by firm assets:

$$Y_{k,t} = \alpha + \beta \times \mathit{Inflex}_j + \gamma \times \mathit{Inflex}_j \times \mathit{VSBY}_{j,t-1} + \delta \times \mathit{VSBY}_{j,t-1} + X'_{k,t-1} \times \theta + \eta_t + \eta_k + \epsilon_{k,t}.$$

For each firm k in year t, $Y_{k,t}$ is measured as the average of daily bid-ask spreads (*Bid-Ask Sprd*), the *PIN* computed by Easley et al. (2002), and *Dispersion*, the percentile rank form of *Raw Dispersion*, which is computed as the standard deviation of two-year-ahead analyst EPS forecasts divided by the absolute value of actual EPS. Inflex_j is the frequency of price adjustment (*FPA*) for each 6-digit NAICS customer sector j, multiplied by -1. $\mathit{VSBY}_{j,t-1}$ is the input-cost visibility for each 6-digit NAICS customer sector j. $\mathit{VSBY}_{k,t}$ and $\mathit{Inflex}_j \times \mathit{VSBY}_{k,t}$ are instrumented by IV and $\mathit{Inflex}_j \times IV$, respectively. IV is $\mathit{Post} \times \Delta \mathit{Rank}_j$. $\Delta \mathit{Rank}_j$ is the percentile-rank-transformed difference between input-cost visibilities in January 2004 and November 2003 ($\Delta VSBY_j$). *Post* is an indicator that equals 1 if year t is after 2004, and 0 otherwise. See Table 2 for detailed descriptions of control variables. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the level of 6-digit NAICS sectors.

Panel A: First Stage

	Bid-Ask Sprd		PIN		Dispersion	
	(1)	(2)	(3)	(4)	(5)	(6)
IV	0.257***	0.035*	0.266***	0.036*	0.257***	0.035*
	(0.044)	(0.019)	(0.047)	(0.020)	(0.044)	(0.019)
IV × Inflex	-0.318***	0.460***	-0.300***	0.459***	-0.318***	0.460***
	(0.084)	(0.032)	(0.085)	(0.032)	(0.084)	(0.032)
Controls	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
N	11,943	11,943	6,085	6,085	9,611	9,611
F-stat	20.23	111.32	17.69	102.89	20.23	111.32

Panel B: Second Stage

	Bid-Ask Sprd	PIN	Dispersion
	(1)	(2)	(3)
VSBY × Inflex	-0.105***	-0.142***	-0.742***
	(0.022)	(0.053)	(0.195)
VSBY	-0.005	-0.123***	-0.517***
	(0.013)	(0.033)	(0.170)
Controls	X	X	X
Firm FE	X	X	X
Year FE	X	X	X
N	11,943	6,085	9,611

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Table A.5: **IV Estimation: First Stage, Continuous Measure**

This table reports the first-stage results for instrumental variable (IV) estimation with continuous treatment of $\Delta\, VSBY_j^{2004}$. The sample period is from July 1997 to June 2013. The sample is restricted to S&P 1500 firms. Utilities and financial sectors are excluded. We estimate the following model, and observations are weighted by firm assets:

$$Y_{k,t} = \alpha + \beta \times \mathit{Inflex}_j + \gamma \times \mathit{Inflex}_j \times VSBY_{j,t-1} + \delta \times VSBY_{j,t-1} + X'_{k,t-1} \times \theta + \eta_t + \eta_k + \epsilon_{k,t}.$$

For each firm k in year t, $Y_{k,t}$ is measured as the average of daily bid-ask spreads (*Bid-Ask Sprd*), the *PIN* computed by Easley et al. (2002), and *Dispersion*, the percentile rank form of *Raw Dispersion*, which is computed as the standard deviation of two-year-ahead analyst EPS forecasts divided by the absolute value of actual EPS. Inflex_j is the frequency of price adjustment (*FPA*) for each 6-digit NAICS customer sector j, multiplied by -1. $VSBY_{j,t-1}$ is the input-cost visibility for each 6-digit NAICS customer sector j. $VSBY_{k,t}$ and $\mathit{Inflex}_j \times VSBY_{k,t}$ are instrumented by IV and $\mathit{Inflex}_j \times IV$, respectively. IV is $\mathit{Post} \times \Delta\, VSBY_j^{2004}$, which is the difference between input-cost visibilities in January 2004 and December 2002 ($\Delta\, VSBY_j^{2004}$). *Post* is an indicator that equals 1 if year t is after 2004, and 0 otherwise. Panel A includes a set of industry (4-digit SIC)- and year-fixed effects. Panel B includes a set of firm- and year-fixed effects. See Table 2 for detailed descriptions of control variables. *Time* is a full set of dummies indicating years. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the level of 6-digit NAICS sectors.

Panel A: Industry- and Year-Fixed Effects

	Bid-Ask Sprd		PIN		Dispersion	
	(1)	(2)	(3)	(4)	(5)	(6)
IV	0.204	0.357***	0.265**	0.361***	0.257**	0.320***
	(0.126)	(0.109)	(0.122)	(0.103)	(0.120)	(0.099)
IV × Inflex	-1.189***	1.610***	-1.112***	1.611***	-1.187***	1.575***
	(0.284)	(0.186)	(0.276)	(0.181)	(0.295)	(0.180)
Controls	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X
N	12,092	12,092	6,131	6,131	9,772	9,772
F-stat	18.27	67.83	17.18	53.95	18.88	70.14

Panel B: Firm- and Year-Fixed Effects

	Bid-Ask Sprd		PIN		Dispersion	
	(1)	(2)	(3)	(4)	(5)	(6)
IV	0.317***	0.254***	0.351***	0.253***	0.346***	0.245***
	(0.119)	(0.092)	(0.115)	(0.086)	(0.116)	(0.085)
IV × Inflex	-1.137***	1.379***	-1.061***	1.366***	-1.127***	1.384***
	(0.291)	(0.159)	(0.306)	(0.152)	(0.301)	(0.154)
Controls	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X
Time FE	X	X	X	X	X	X
N	11,943	11,943	6,085	6,085	9,611	9,611
F-stat	20.43	76.92	18.11	63.62	21.04	76.3

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Table A.6: **IV Estimation: Second Stage, Continuous Measure**

This table reports the second-stage results for instrumental variable (IV) estimation with continuous treatment of $\Delta VSBY_j^{2004}$. The sample period is from July 1997 to June 2013. The sample is restricted to S&P 1500 firms. Utilities and financial sectors are excluded. We estimate the following model, and observations are weighted by firm assets:

$$Y_{k,t} = \alpha + \beta \times \mathit{Inflex}_j + \gamma \times \mathit{Inflex}_j \times VSBY_{j,t-1} + \delta \times VSBY_{j,t-1} + X'_{k,t-1} \times \theta + \eta_t + \eta_k + \epsilon_{k,t}.$$

For each firm k in year t, $Y_{k,t}$ is measured as the average of daily bid-ask spreads (*Bid-Ask Sprd*), the *PIN* computed by Easley et al. (2002), and *Dispersion*, the percentile rank form of *Raw Dispersion*, which is computed as the standard deviation of two-year-ahead analyst EPS forecasts divided by the absolute value of actual EPS. Inflex_j is the frequency of price adjustment (*FPA*) for each 6-digit NAICS customer sector j, multiplied by -1. $VSBY_{j,t-1}$ is the input-cost visibility for each 6-digit NAICS customer sector j. $VSBY_{k,t}$ and $\mathit{Inflex}_j \times VSBY_{k,t}$ are instrumented by IV and $\mathit{Inflex}_j \times IV$, respectively. IV is $Post \times \Delta VSBY_j^{2004}$, which is the difference between input-cost visibilities in January 2004 and December 2002 ($\Delta VSBY_j^{2004}$). *Post* is an indicator that equals 1 if year t is after 2004, and 0 otherwise. See Table 2 for detailed descriptions of control variables. *Industry* is a full set of dummies indicating 4-digit SIC industries. *Time* is a full set of dummies indicating years. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the level of 6-digit NAICS sectors.

	Bid-Ask Sprd		PIN		Dispersion	
	(1)	(2)	(3)	(4)	(5)	(6)
Inflex	0.038***		0.075**		0.483*	
	(0.013)		(0.030)		(0.285)	
Inflex × VSBY	-0.084***	-0.095***	-0.100**	-0.119**	-0.996***	-0.702***
	(0.022)	(0.025)	(0.042)	(0.056)	(0.275)	(0.232)
VSBY	0.000	-0.007	-0.111***	-0.120***	-0.710***	-0.521***
	(0.014)	(0.013)	(0.035)	(0.036)	(0.205)	(0.162)
Controls	X	X	X	X	X	X
Time FE	X	X	X	X	X	X
Industry FE	X		X		X	
Firm FE		X		X		X
N	12,092	11,943	6,131	6,085	9,772	96,11

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Table A.7: **IV Estimation: Coarser BEA Industry Classifications**

This table reports the first-stage and second-stage results for instrument variable (IV) estimation when cost visibility is constructed for coarser BEA industry classifications. The sample period is from July 1997 to June 2013. The sample is restricted to S&P 1500 firms. Utilities and financial sectors are excluded. We estimate the following model, and observations are weighted by firm assets:

$$Y_{k,t} = \alpha + \beta \times Inflex_j + \gamma \times Inflex_j \times VSBY_{h,t-1} + \delta \times VSBY_{h,t-1} + X'_{k,t-1} \times \theta + \eta_t + \eta_k + \epsilon_{k,t}.$$

For each firm k in year t, $Y_{k,t}$ is measured as the average of daily bid-ask spreads (*Bid-Ask Sprd*), the *PIN* computed by Easley et al. (2002), and *Dispersion*, the percentile rank form of *Raw Dispersion*, which is computed as the standard deviation of two-year-ahead analyst EPS forecasts divided by the absolute value of actual EPS. $Inflex_j$ is the frequency of price adjustment (*FPA*) for each 6-digit NAICS customer sector j, multiplied by -1. $VSBY_{h,t-1}$ is the input-cost visibility for each coarser BEA industry classification h. $VSBY_{h,t-1}$ and $Inflex_j \times VSBY_{h,t-1}$ are instrumented by IV and $Inflex_j \times IV$, respectively. IV is $Post \times \Delta Rank_h$. $\Delta Rank_h$ is the percentile-rank-transformed difference between input-cost visibilities in January 2004 and December 2002 ($\Delta VSBY_h$). *Post* is an indicator that equals 1 if year t is after 2004, and 0 otherwise. See Table 2 for detailed descriptions of control variables. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the level of 6-digit NAICS sectors.

Panel A: First Stage

	Bid-Ask Sprd		PIN		Dispersion	
	(1)	(2)	(3)	(4)	(5)	(6)
IV	0.294***	-0.010	0.285***	-0.016	0.287***	-0.005
	(0.035)	(0.016)	(0.040)	(0.019)	(0.034)	(0.012)
IV × Inflex	0.238*	0.221***	0.228	0.192**	0.208*	0.236***
	(0.122)	(0.066)	(0.167)	(0.090)	(0.115)	(0.059)
Controls	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
N	11,770	11,770	5,980	5,980	9,592	9,592
F-stat	45.7	34.33	40.67	17.48	44.5	37.39

Panel B: Second Stage

	Bid-Ask Sprd	PIN	Dispersion
	(1)	(2)	(3)
Inflex × VSBY	-0.278***	-0.245*	-2.059***
	(0.103)	(0.130)	(0.587)
VSBY	-0.025	-0.117***	-0.187
	(0.032)	(0.043)	(0.211)
Controls	X	X	X
Firm FE	X	X	X
Year FE	X	X	X
N	11,770	5,980	9,592

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Table A.8: **An Example of Concordance between NAICS and SIC**

This table illustrates the concordance between the 2002 North American Industry Classification System (NAICS) and the 1987 Standard Industrial Classification System (SIC) in the Producer Price Index (PPI) program compiled by the Bureau of Labor Statistics (BLS). Panel A presents the concordance for the Petroleum and Coal Products Manufacturing sector. Panel B presents the concordance for the Textile Mills sector.

Panel A: Petroleum and Coal Products Manufacturing

NAICS	Product Name	SIC
324110	Petroleum refineries	2911
324110P	Primary products	2911P
3241101	Gasoline, including finished base stocks and blending agents	29111
324110111	Aviation gasoline (except jet fuel) incl finished base stocks & blending agents	2911111
32411013	Motor gasoline, including finished base stocks and blending agents	291113
324110134	Regular gasoline	2911134
324110135	Mid-premium gasoline	2911135
324110136	Premium gasoline	2911136
3241102	Jet fuel	29112
3241103	Kerosene, except jet fuel	29113
3241104	Light fuel oils	29114
324110411	Home heating oil and other distillates, NEC	2911411
324110413	Diesel fuel	2911413
3241105	Heavy fuel oils, including No. 5, No. 6, heavy diesel, gas enrichment oils, etc.	29115
3241107	Lubricating oil and greases, made in a refinery	29117
3241108	Unfinished oils and lubricating oil base stock	29118
3241109	Asphalt	29119
324110A	Liquefied refinery gases, including other aliphatics (feed stock and other uses)	2911A
324110D	Other finished petroleum products, including waxes	2911D
324110SM	Secondary and miscellaneous products	2911SM
324110M	Miscellaneous receipts	2911M
324110S	Secondary products	2911S

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Panel B: Textile Mills

NAICS	Product Name	SIC
313311	Broadwoven fabric finishing mills	
313311P	Primary products	
3133111	Finished cotton broadwoven fabrics (not finished in weaving mills)	22617
3133113	Job or commission finishing of cotton broadwoven fabrics	22619
3133115	Finished manmade fiber & silk broadwoven fabrics (not finished in weaving mills)	22628
3133117	Job or commission finishing of manmade fiber and silk broadwoven fabrics	22629
3133119	Finished broadwoven wool fabrics and felts (not finished in weaving mills)	
313311SM	Secondary products and miscellaneous receipts	
313311M	Miscellaneous receipts	
313311S	Secondary products	
313312	Textile/fabric finishing (exc broadwoven) mills	
313312P	Primary products	
3133121	Finished fabrics (except broadwoven) and other finished textiles	
313312SM	Secondary products and miscellaneous receipts	
313312M	Miscellaneous receipts	
313312S	Secondary products	
313320	Fabric coating mills	2295
313320P	Primary products	2295P
3133201	Vinyl coated fabrics, including expanded vinyl coated	22952
3133203	Rubber coated fabrics	
3133205131	Pyroxylin and polyurethane coated fabrics	2295316
3133205491	Other coated or laminated fabrics, excluding rubberized fabrics	2295322
313320SM	Secondary products and miscellaneous receipts	2295SM
313320M	Miscellaneous receipts	2295M
313320S	Secondary products	2295S

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Table A.9: **Adoption of Universal Demand (UD) Laws**

State Name	Adoption Year	# Obs	
		Before	After
Georgia	1989	0	335
Michigan	1989	0	277
Florida	1990	0	328
Wisconsin	1991	0	418
Montana	1992	0	8
Virginia	1992	15	444
Utah	1992	1	102
New Hampshire	1993	0	0
Mississippi	1993	2	41
North Carolina	1995	36	232
Arizona	1996	0	33
Nebraska	1996	11	33
Connecticut	1997	42	83
Maine	1997	5	3
Pennsylvania	1997	170	359
Texas	1997	81	285
Wyoming	1997	0	9
Idaho	1998	0	0
Hawaii	2001	10	16
Iowa	2003	58	40
Massachusetts	2004	341	168
Rhode Island	2005	41	7
South Dakota	2005	3	7

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