Downward nominal price rigidity and earnings quality[#]

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Abstract

I provide the first evidence that firms' sluggishness in adjusting downward the selling prices of their outputs impairs the quality of accounting earnings. Using a unique data set and a novel approach to measure the impact of industry-wide input costs on output prices, I show three sets of results. First, operating earnings become much less persistent for firms receiving negative input cost shocks than for those receiving positive ones of the same magnitude. The result holds primarily for industries in which input costs are expected to inflate. Second, the impact of input cost deflation on earnings persistence is partially offset by earnings smoothing and manifests itself in a timelier manner on operating cash flows than on accruals. Third, security analysts adjust their estimation about the persistence of earnings shocks more slowly following cost deflations than inflations, which explains the difference in the post-earnings announcement drift across firms.

JEL Classification: E31, G10, M41

Keywords: Downward nominal price rigidity; Fuzzy regression discontinuity design; Earnings quality

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1. Introduction

This paper provides the first evidence that firms' sluggishness in adjusting downward the selling prices of their outputs impairs the quality of accounting earnings. According to the new classical theory, price changes should be made in response to cost increases and cost decreases at the same pace and by the same magnitude.[1] In real life, however, prices rise faster than they fall in response to shocks to input costs. The economic literature refers to this phenomenon as downward nominal price rigidity.[2] When input costs decrease but firms postpone reducing output prices, a temporary mismatch arises between revenues and cost of goods sold. Such a mismatch causes current accounting earnings to be less informative about firms' permanent earnings.

To operationalize this idea, I use a firm's operating profit margin (i.e., operating income divided by sales) as the primary measure of earnings. With industry-level price data from the Bureau of Labor Statistics (BLS), I construct a measure of the time-varying impact of input cost inflation or deflation on output prices. I show that the persistence of both operating margin and return on assets (ROA) for firms experiencing cost deflation is lower than that of firms experiencing cost inflation of the same magnitude. I also find that the impact of input cost deflation on earnings persistence is partially offset by earnings smoothing and manifests itself in a timelier manner on operating cash flows than on accruals. Last, security analysts adjust their estimation about the persistence of earnings shocks more slowly following cost deflations than inflations, which explains the difference in the post-earnings announcement drift (PEAD) across

[1] The optimal price for a monopolistic competitive firm is a constant markup times marginal cost (Dixit and Stiglitz, 1977). As Peltzman (2000, p. 467) states: "Economic theory suggests no pervasive tendency for prices to respond faster to one kind of cost change than to another. In the paradigmatic price theory we teach, input price increases or decreases move marginal costs and then prices go up or down symmetrically and reversibly."

[2] Economic studies document the phenomenon in gasoline (Borenstein et al., 1997), agricultural products (Karrenbrock, 1991), bank deposit rates (Hannan and Berger, 1991; Neumark and Sharpe, 1992), and retail products (Chen et al., 2008; Peltzman, 2000). See also "The great pork gap: Hog prices have plummeted; Why haven't store prices?" (*New York Times*, January 9, 1999).

firms. The last finding suggests that, when prices are rigid, firms' private information about changes in their input costs cannot be fully revealed, implying information asymmetry in the financial market.[3]

The issue of how changes in the nominal price level are linked to earnings quality has attracted much academic and regulatory attention. On the academic side, prior studies documented the failure of the financial reporting to reflect the impact of inflation on US corporate earnings, especially during the late 1970s when the inflation rate was extremely high (e.g., Beaver et al., 1980; Beaver et al., 1982; Hughes et al., 2004; Konchitchki, 2011, 2013; Shoven and Bulow, 1975; Watts and Zimmerman, 1980). Most of the studies were conducted with a widely held belief that inflation creates an earnings illusion, as expenses based on the allocation of historical costs are mismatched with revenues. On the regulator side, the Financial Accounting Standards Board (FASB) mandated the disclosure of the impact of inflation on financial statements (e.g., current cost of assets).[4]

Instead of connecting earnings quality with fluctuations in the general consumer price index (CPI) through accounting practices (i.e., historical cost accounting), this paper departs from prior studies by incorporating firms' operating decisions (i.e., how to absorb nominal shocks to input costs) as an economic driver of earnings quality.[5] As a result, the paper is more relevant to a modern economy in which aggregated inflations are at moderate levels. The relevance of this issue to today's financial statement users is best illustrated by a November 14, 2008 *Wall Street*

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[3] Input cost shocks can have two parts: industry-level components and idiosyncratic components. Legitimate reasons exist for the idiosyncratic components to be firms' private information. For example, each firm can negotiate with its suppliers to share losses or profits caused by cost shocks, but the negotiation outcome is not publicly disclosed. Another example, both private and public firms are participants of BLS's monthly survey. However, the averaged index released does not perfectly reflect how much a public firm is affected. See Xie and Xu (2015) for a theoretical framework about the mechanism.

[4] In 1979, FASB released the Statement of Financial Accounting Standard (SFAS) 33, which mandated that public firms restate income by adjusting the effects of general inflation. SFAS 33 is no longer in effect.

[5] The term "inflation" used in this paper differs from the general consumer price index as emphasized by the prior literature.

Journal article which expressed its concern over Wal-Mart's future performance. According to the article, although Wal-Mart's earnings for the third quarter of 2008 rose 9.8%, the retail giant's sales improvement in the wake of the financial crisis was due to a transitory lift from federal stimulus checks and from the sale of food, which was priced higher than the year before partly due to inflation.

Part of the reason that Wal-Mart's earnings were transitory is that, in response to the weakening of the economy, the company lagged in cutting prices. The rate of food cost inflation in the United States peaked at 6% in the spring of 2008, but it plunged sharply during the subsequent recession period, with effective food cost deflation by the end of 2009.[6] However, Wal-Mart did not start planning an aggressive campaign to cut prices on thousands of its products until after April 2010.[7] This example delivers an important message: When a downward price adjustment is delayed, firms' current financial statements become less informative of their future performance.

I develop the main hypothesis based on the theory of asymmetric price adjustment laid out by Ball and Mankiw (1994). They establish that, with costly price adjustment and trend inflation (i.e., expected inflation in input costs), a firm has more incentives to delay a downward price adjustment compared with an upward price adjustment. When a firm wants a lower relative price on a product, it does not need to immediately impose a costly price adjustment, because trend inflation largely takes care of the matter.[8] I derive from the theory the implication of the downward nominal price rigidity for earnings persistence. I demonstrate that a temporal

[6] See http://www.tradingeconomics.com/united-states/food-inflation.

[7] The *Wall Street Journal* on April 9, 2010 reported that Wal-Mart was cutting prices on roughly 10,000 items, mostly food and other staples.

[8] A quick price response is costly because managers have to acquire information about demand and because customers will become angry or confused about a sudden change in price. See Section 2 for further discussion.

mismatch of revenues with costs leads to a rise followed by a fall of the transitory profit margin in firms experiencing deflation in input costs, reducing the persistence of their earnings.[9]

An empirical challenge to testing the prediction is how to measure the extent to which price adjustments are delayed. Raw inflation data cannot be used for two reasons. First, many long-term contracts include clauses that automatically, and therefore costlessly, trigger price adjustments (or renegotiations) whenever inflation surpasses a certain rate. Thus, raw inflation data include a component of measurement error. Second, the fact that a downward-sloping demand curve is industry-specific suggests that cross-sectional differences exist in how prices respond to the same unit of input cost shock.

To measure the impact of industry-wide input cost inflation or deflation on output price, I use a unique combination of input-output structures [collected from the Bureau of Economic Analysis (BEA)] and a price data set (collected from BLS). I then exploit the impulse response of output prices to input cost shocks, estimated from a vector autoregression (VAR) system, to construct a price divergence variable. This variable captures the direction and magnitude in which changes in output price deviate from its long-run equilibrium level due to nominal price rigidities.[10] A positive price divergence means that current prices are too high relative to the long-run equilibria, and vice versa. I verify that, in response to the measured price divergence, output prices rise faster than they fall in industries that cover a majority of US public firms. Furthermore, the asymmetry occurs only when expected inflation in input costs is positive, consistent with the predictions of Ball and Mankiw (1994).

[9] Although price rigidity following a reduction in input costs clearly increases a firm's profit margin, whether it implies a transitory increase or decrease in earnings is uncertain. This depends on the firm's demand elasticity, as well as reactions from industry peers. However, earnings will become less persistent as long as the transitory profit margin is eliminated by a price adjustment in the future.

[10] The terms "long-run equilibrium price" and "optimal price" are used interchangeably in the paper. Optimal price refers to the price level at which profits are re-maximized after cost shocks. When a quick price adjustment by the full amount is perceived as costly, firms smooth their adjustments over time and optimal price is achieved in the long run.

To examine the impact of downward price rigidity on earnings quality, I use a fuzzy regression discontinuity design (FDD). FDD addresses the concern that earnings quality, cost inflation, and other confounding effects may be jointly determined. While the distributions of other firm characteristics around a certain cutoff are smooth, FDD requires a discontinuous jump in the probability of treatment effect (i.e., the occurrence of price adjustment) if the so-called forcing variable (i.e., price divergence) crosses this cutoff. To implement FDD, I assign the treatment and control groups to firm-year observations with price divergences lying closely on the positive and negative sides of the cutoff point. In this way, I can estimate the true impact of downward price rigidity on earnings quality by comparing the outcome of the treatment group with that of the control group.

My empirical results are fourfold. First, the downward nominal price rigidity has a negative and significant impact on the persistence of operating earnings. Such an impact grows progressively larger as time passes. The price adjustment in response to cost deflation lags behind that in response to cost inflation for about one year. The downward nominal price rigidity thus impacts earnings quality mainly through reducing the two-year-ahead (and onward) earnings persistence. Second, the findings hold primarily for industries in which input costs are expected to inflate. This is consistent with the theoretical prediction of Ball and Mankiw (1994) that prices are downward rigid simply because firms free ride on trend inflation to save adjustment costs. Third, the reduction in earnings persistence is most pronounced in operating cash flows than accruals, which is partially due to earnings smoothing by firm management. Fourth, perhaps more surprisingly, when prices are downward rigid, security analysts are faced with information frictions. For example, they are slow in incorporating the persistence of previously announced earnings news into the two-year-ahead earnings forecasts. The resulting forecast errors are corrected over time following quarterly earnings announcements. Such a correction leads to a negative PEAD.

My study contributes to several strands of the literature. First, the paper offers a new interpretation for why accounting earnings fail to reflect firms' economic performance when nominal price levels fluctuate. Extant literature studies this issue from the perspective of historical cost accounting (Beaver et al., 1980; Beaver et al., 1982; Hughes et al., 2004; Konchitchki, 2011, 2013; Watts and Zimmerman, 1980). Under the prevailing financial reporting system in the US, a mismatch of nominal revenues and historical costs can overstate accounting earnings during periods of high inflation. However, prior studies are silent on the implications of a moderate inflation or deflation environment for earnings quality.[11] By emphasizing nominal price rigidity, I show that even low inflation rates can have a nontrivial impact on earnings quality. The attention of both practitioners (e.g., investors, banks, and analysts) and standard setters (e.g., FASB) is called to the implication of inflation for financial reporting.

Second, the paper relates to, but differs from, the literature on the implication of inflation for market efficiency. Prior studies link inflation to stock returns to test the money illusion hypothesis developed by Modigliani and Cohn (1979). The authors hypothesize that investors tend to think of value in nominal terms and capitalize real earnings growth at a nominal interest rate. Consistent with the money illusion hypothesis, Chordia and Shivakumar (2005) and Basu et al. (2010) find that inflation is strongly positively associated with PEAD. The authors argue that their findings are consistent with stocks with earnings growth that is positively related to inflation is undervalued and vice versa. In contrast, my study offers a rational perspective to

[11] Historical cost accounting refers to the fact that assets and liabilities are shown at their historical cost. So, for a mismatch between gross income and costs (e.g., interest expenses and depreciations) to substantially reduce earnings quality, inflation rates affecting current costs must be high enough. However, the mismatch between revenues and costs under nominal price rigidities does not require high inflation or deflation rates. The effect of a delayed response of output price to a series of moderate input cost shocks will be large enough.

understand the relation between inflation and stock market efficiency, especially when earnings news is announced. That is, when adjustments of output prices in response to input cost inflation or deflation are delayed, firms' private information about changes in both their input costs and units to be sold is not quickly revealed. This exacerbates information asymmetry in the financial market and reduces stock price efficiency. I find that, after cost deflation arrives, analyst forecast errors positively respond to previously announced earnings surprises, which is responsible for the differential impact of inflation versus deflation on PEAD.

Third, employing cost inflation as a driver, the paper contributes to the literature on the economic determinants of earnings quality. In their survey of earnings quality literature, Dechow et al. (2010, p.391)stated: "[W]e are not aware of studies about a firm's earnings-related accounting choices when the anticipated impact of the choice on earnings properties is limited because the property is primarily driven by the firm's fundamental performance." The scarcity of this line of academic research contrasts to the real-world consensus among corporate chief financial officers that, as determinants of earnings quality, economic factors are equally as important as accounting standards (Dichev et al., 2013). My findings on firms' earnings smoothing in response to deflation in input costs, as well as a less timely reflection of accruals on a reduction in earnings persistence, provide evidence that both earnings quality and accounting choice are strongly influenced by economic forces determining firms' economic performance.

Fourth, the paper adds to the recent growing literature on macro accounting, which offers analysis in two opposite directions. One direction is from macro to micro. For example, Li et al. (2014) use a macro factor to predict firms' accounting information, and they find that combining firm-level exposures to foreign countries (via geographic segment data) with forecasts of country-level performance can generate superior forecasts for firm fundamentals. Similar in spirit to Li et al., I study how inflation, another important macro factor, informs accounting results of individual firms. The other direction is from micro to macro, e.g., how earnings of individual firms reveal macro activity. Konchitchki and Patatoukas (2014) and Konchitchki et al. (2015) find that accounting inputs such as aggregate accounting earnings growth, or auditors' going concern opinion, is a leading indicator of growth in nominal gross domestic product (GDP). By linking pricing behavior and earnings persistence at the firm level, my study also extends this area of research and confirms the microfoundation of the asymmetrical impact of monetary shocks on output (e.g., Cover, 1992).

The rest of the paper is organized as follows. Section 2 develops the main hypothesis. Section 3 describes the construction of data. Section 4 introduces the construction of the main independent variable and the fuzzy regression discontinuity design. Section 5 presents the empirical results. Section 6 concludes.

2. Theoretical framework

2.1 Theoretical framework and hypothesis

In this subsection, I present my main hypothesis based on the key results derived from the theory of asymmetric price adjustment proposed by Ball and Mankiw (1994). In their model, two main assumptions drive the results. First, a firm can freely adjust its selling price at the beginning of each price cycle, but it has to pay a menu cost in response to nominal shocks to input costs during the cycle. The term "menu cost" originated with the price that restaurants paid to print new menus. However, it is now commonly used to refer to the costs of changing nominal prices. Examples of menu costs range from customers' unfavorable reactions to frequent price changes to the time and attention required of managers to make pricing decisions (see, e.g., Blinder et al., 1998; Kleshchelski and Vincent, 2009; and Mankiw and Reis, 2002, among others).[12] Second, firms' input costs are expected to inflate. This assumption not only captures a fact of life but also provides a necessary condition for price adjustments to be downward rigid.

The original framework in Ball and Mankiw (1994) does not have any implications for the time series property of profits. I thus augment their model with earnings process so that asymmetric price adjustment can be linked to asymmetric earnings persistence. Consider a profit-maximizing firm, whose economic life consists of multiple price cycles. Each price cycle has two periods—an even period and an odd period. The firm can freely adjust its price at the beginning of each even period, but it has to pay a cost of K to adjust at the beginning of each odd period. The timeline of the framework is outlined in Fig. 1. The firm's demand curve at time *t* is given by

$$Q_t = BP_t{}^{-\rho}, B, \ \rho > 0, \tag{1}$$

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. It is easy to show that the optimal selling price at time *t* is $P_t^* = \Lambda C_t$, where $\Lambda = \frac{\rho}{\rho-1}$. However, C_t is expected to increase by an amount equal to Π % at the end of time *t*, when the realized input cost turns out to be $\Pi \times E_t$ percent. E_t is the shock to input costs, which is unexpected by the firm.[13] Thus, the optimal price at time *t*+1 is $P_{t+1}^* = \Lambda \times \Pi \times E_t \times C_t$.

[Insert Fig. 1 near here]

[12] A costless adjustment is often referred to as a time-contingent adjustment, which is found in a staggered price setting. That is, different firms, for some exogenous reasons, plan to maintain certain price levels over different time intervals. A costly adjustment involves special adjustments within a prescheduled time interval.

[13] The results are obtained under the assumption that the firm acts as if the probability of future cost shocks is zero. By following Ball and Mankiw (1994) I show that the result in Eq. (10) is robust to the inclusion of a distribution function of ϵ_t.The results are available upon request.

In even period *t*, the firm, which neglects discounting, sets the initial selling price to minimize the following two-period quadratic loss function in which a gap between actual and optimal prices is penalized:

$$\min_p (p_t - p_t^*)^2 + \mathbb{E}_t(p_t - p_{t+1}^*)^2. \tag{2}$$

$p_t, p_t^* = c_t + \lambda$ and $p_{t+1}^* = p_t^* + \pi + \epsilon_t$ are the log forms of P_t , P_t^*, and P_{t+1}^*. The problem in Eq. (2) is equivalent to a profit-maximizing problem if a general profit function is taken a second-order approximation (Ball and Romer, 1989). In other words, any deviation of actual price from the optimal price reduces firm profits. It is easy to calculate that the price at time *t* that the firm would set is

$$p_t^{**} = c_t + \lambda + \frac{1}{2}\pi. \tag{3}$$

In Eq. (3), with both menu cost and trend inflation, price in time *t* is set with an upward bias relative to p_t^* , the frictionless optimal.

In the odd period of *t*+1, the firm decides whether to pay a cost K to minimize the following one-period loss function:

$$(p_t^{**} - p_{t+1}^*)^2. \tag{4}$$

Given $c_{t+1} = c_t + \pi + \epsilon_t$, the firm refuses to adjust if $K > (p_t^{**} - p_t^* - \pi - \epsilon_t)^2$. This condition leads to the following asymmetric range of inaction in which the firm does not adjust:

$$\epsilon_t \in [-\sqrt{K} - \frac{1}{2}\pi,\ \sqrt{K} - \frac{1}{2}\pi\ ]. \tag{5}$$

In time *t+2*, a new even period, the mechanism repeats. Eq. (5) implies that a change in price is trigged by a small positive cost shock and that price is rigid for a much larger range of input cost decreases. The upward bias of $\frac{1}{2}\pi$ makes the firm lose less (more) profits after deflation (inflation) shocks hit.[14]

Next, I derive the main hypothesis of the paper based on Eqs. (3) and (5). The firm's profit margin in time *t*+1 conditioning on whether price adjustment occurs is

$$\theta_{t+1} = \lambda + (A-1)(\tfrac{1}{2}\pi + \epsilon_t). \tag{6}$$

A is an indicator variable equal to one if the firm adjusts and zero if it does not. I also assume that the expected inflation in input costs as of *t*+2 is still π. Because a firm can adjust price freely in the beginning of period *t*+2, $p^{**}_{t+2} = p^*_t + \frac{1}{2}\pi$ and $\theta_{t+2} = \lambda + \frac{1}{2}\pi$.[15] Conditioning on whether adjustment occurs in *t*+1, the earnings persistence coefficient can be calculated based on the variance of θ_{t+1}:

$$var(\theta_{t+1}) = \sigma_\lambda^2 + (1-A)(\tfrac{1}{4}\sigma_\pi^2 + \sigma_\epsilon^2), \tag{7}$$

and the covariance between θ_{t+1} and θ_{t+2} is

$$cov(\theta_{t+1}, \theta_{t+2}) = \sigma_\lambda^2 + (A-1)\tfrac{1}{4}\sigma_\pi^2\ , \tag{8}$$

where σ_λ^2, σ_π^2, and σ_ϵ^2 are the variances of λ, π, and ϵ, respectively. I assume that firms are eventually distributed over the interval of ϵ_t. Suppose N firms are experiencing cost increases and another N firms are experiencing cost decreases. In addition, the number of non-adjusting firms are N_1 and N_2, respectively. Based on Eq. (5), it is easy to show that

$$\mu_1 = \frac{N1}{N} < \frac{N2}{N} = \mu_2. \tag{9}$$

[14] At first glance, the asymmetry seems to be caused only by the upward bias. However, the upward bias itself is a result of the firm avoiding a costly prompt response to cost shocks. In addition, if adjustment cost is zero, a firm will always adjust despite the sign or magnitude of a cost shock. In this case, the asymmetric inaction regime does not exist.

[15] This captures the long-run neutrality of monetary effect. That is, when wages are increased to fully compensate customers or when consumers charge a price high enough to their own customers, the demand curve facing the firm shifts outward as B grows so that the effect of cost changes on nominal profits will be fully eliminated.

The theoretical earnings persistence coefficient conditioning on the sign of input cost shock can be expressed as

$$\mathrm{plim}_{N\to\infty}\,\beta = \begin{cases} \beta^{+} = \frac{(1-\mu_1)cov(\theta_{t+1},\theta_{t+2}|A=1)+\mu_1 cov(\theta_{t+1},\theta_{t+2}|A=0)}{(1-\mu_1)var(\theta_{t+1}|A=1)+\mu_1 var(\theta_{t+1}|A=0)}, & if\ \epsilon_t \geq 0 \\ \\ \beta^{-} = \frac{(1-\mu_2)cov(\theta_{t+1},\theta_{t+2}|A=1)+\mu_2 cov(\theta_{t+1},\theta_{t+2}|A=0)}{(1-\mu_2)var(\theta_{t+1}|A=1)+\mu_2 var(\theta_{t+1}|A=0)}, & if\ \epsilon_t < 0 \end{cases}. \qquad (10)$$

It is easy to verify that $\beta^{+} > \beta^{-}$. Eq. (10) suggests that downward nominal price rigidity translates symmetrically distributed input cost shocks into asymmetrically distributed transitory earnings, with the implication that earnings are less persistent for firms experiencing input cost decreases than for those experiencing input cost increases.

H1: Ceteris paribus, the persistence of earnings is lower for firms experiencing unexpected input cost decreases than for firms experiencing unexpected input cost increases of the same magnitude. This occurs only when expected inflation in input costs is positive.

2.2 An illustrative example

To better understand the mechanism driving downward price rigidity, I apply the key results of the framework to a real-life example. Suppose Cal-Maine Foods, a producer and marketer of shell eggs, enters into a five-year supply contract with Wal-Mart Stores. Cal-Maine Foods derives a substantial portion of revenues from supplying Wal-Mart with shell eggs. According to the results in Subsection 2.1, the egg firm's economic incentive to adopt a flexible price schedule is expressed as the distance between the short-run and long-run equilibrium (or optimal) selling prices.

To make the example more generalizable, menu cost takes the form of the cost of information acquisition. For example, managers of Cal-Maine Foods are imperfectly informed about the impact of input cost changes on egg prices and need to acquire more information to make pricing decisions. If the egg company wants to pay less to adjust prices, it can wait to act until after receiving clearer signals from consumers or competitors. Menu costs can also take specific forms depending on the sign of input cost shock. In the case of input cost inflation, raising egg prices charged to Wal-Mart within the contracted interval will make the retail giant unhappy with the supplier. In the case of cost deflation, Cal-Maine Foods will be restricted from cutting prices. For example, a sudden decline in price might make customers wary about product quality. In both scenarios, the egg supplier can save the menu costs by delaying the adjustment of egg prices.

To see how egg prices are downward rigid, assume that, before signing the five-year agreement, the two companies anticipate that the cost of hen feed, a major input cost for egg producers, will increase by 15% (which is π in the framework) three years later. Cal-Maine Foods therefore increases the prescheduled price by 7.5% (the upward bias of $\frac{1}{2}\pi$) to minimize the probability of costly adjustments in the future. Under these conditions, if hen feed costs increase by 20% in the third year, Cal-Maine Foods will be hit by a 20 – 15 = 5% cost shock, and the company's benefit to adjust is $(0.2 - 0.075)^2 = 15.6 \times 10^{-3}$. If hen feed costs increases by 10% after three years, the input cost shock will be -5%. Thus, the company's benefit of adjusting is only $(0.10 - 0.075)^2 = 0.625 \times 10^{-3}$. Given adjustment costs, Cal-Maine Foods is more willing to adjust the price it charges to Wal-Mart upward than downward. Thus, the egg company's earnings persistence is reduced more by an unexpected decrease, not an increase of the same size, in hen feed costs.

3. Data

3.1 Product Price and Input Cost

To construct inflation rates for output prices and input costs, I require the nominal prices of input or output, as well as the composition of inputs for the production of output (input-output structure). I use the benchmark input-output (I-O) accounts that show the inputs to industry production and the commodities that are consumed by the final users. BEA published the information every year from 1998 to 2011. To reduce measurement errors, I use the Direct Requirements Use Tables that show the amount of a commodity input directly required by an industry j to produce a certain dollar amount of output in industry i. I measure the input-output structure by calculating the commodity input from each industry j as a percentage of industry intermediates that are utilized by industry i to produce output.[16]

To measure the nominal prices of input commodities, I hand-collect the industry monthly Producer Price Index (PPI) from BLS. The industry classification is based on the three-digit North American Industry Classification System (NAICS). The PPI concerns the output of all industries in the goods-producing sectors of the US economy. Each component is a monthly index of the national average nominal price for some producer good. The price index for each good pertains to the first transaction between firms after the production of the good. Based on inferences from the input-output structures, I determine the degree to which these producer goods contribute to the production of others within each NAICS industry. I match monthly commodity price changes in each input-output industry using the concordance tables between the three-digit NAICS codes and the I-O industry codes.[17] Thus, in an economy that consists of n

[16] I consult the use table published in 1997 for the sample period 1993–1997. Thus, the measure is less likely to be noisy, because the I-O use tables were published every five years before 1998. This fact suggests that the way in which each industry i produces has been relatively stable at least within five years.

[17] However, the release of some price indexes under the three-digit NAICS codes began only in recent years, making the match between I-O tables and PPI incomplete over the sample period of 1993–2011. Therefore, in months when the commodity price changes under three-digit NAICS codes are not available, I use the average price changes of commodities under the four-digit codes as a proxy. If the four-digit data are still not available, I use the average price changes of all of the five-digit commodities to proxy for the four-digit one, and so on.

industries supplying each industry *i*, I calculate the monthly growth rate in input costs, π_{is}^{c}, for downstream industry *i* of each month *s* as

$$\pi_{is}^{c} = \sum_{j=1}^{n} \lambda_{ijs} \, \pi_{js}^{p} \, , \qquad (11)$$

where λ_{ijs} is the commodity input from upstream industry *j* as a percentage of total industry intermediates that are directly consumed by industry *i* as of month *s*. π_{js}^{p} is the monthly growth rate of input commodity produced by upstream industry *j* as of month s.[18]

Because many categories of price index have just recently been recorded by BLS, I focus only on downstream industries with a complete set of price information from 1993 through 2011, including agriculture, forestry, fishing and hunting, mining, utilities, manufacturing, wholesale trade, retail trade, and transportation and warehousing. Moreover, to maintain a complete set of price information from upstream industries to construct input costs, I search for surrogates of prices of upstream industries that have raw price information missing. For example, because a variety of service industries heavily supply downstream, I use monthly wage data extracted from the BLS Current Employment Statistics national survey Employment, Hours, and Earnings to measure the costs for a downstream industry to purchase these services.[19]

3.2 Compustat, CRSP, I/B/E/S

The sample contains all firm-year data for US domestic public companies in the Compustat database for the period 1998–2011. Domestic public companies are those with their main headquarters in the same US state as their state of incorporation. Because both input costs and output prices are available from survey data about the US economy, focusing on domestic

[18] Wage expenditure accounts for a large fraction of total input in many industries. However, wage is most likely to be linked with CPI, and less variation in wage rigidities should exist across industries. I therefore consider only material inputs.

[19] Peltzman (2000) adopts a similar methodology. He aggregates some appropriate PPIs into a single input cost to explain the movement of output PPIs. However, he analyses only those outputs in which a single input accounts for more than 20% of an output's value.

companies improves the accuracy of the estimation. This is especially the case when foreign companies purchase materials from other segmented markets where neither the input-output structure nor the price level is similar to that of the US market. All of the financial data are extracted from the Compustat industrial annual file. Stock return and analyst forecasts data are separately extracted from the Center for Research in Security Prices (CRSP) and Institutional Brokers' Estimate System (I/B/E/S).

4. Estimation approach and econometric issues

4.1 Estimating the price impact of cost shocks

Empirically, the most challenging task is determining how to measure the extent to which product prices are delayed upon the arrival of cost shocks. The raw inflation data as constructed in Eq. (2) cannot be directly used for several reasons. First, many price contracts are imperfectly indexed to inflation and prices may be partially but freely adjusted upon the arrival of inflation. This fact mitigates the impact of inflation on prices. To reduce measurement errors, the portion of price inflation owning to inflation indexation must be excluded. Second, the relationship between price and cost changes is not one-to-one, as the demand curve is downward-sloping and its steepness varies across industries. Unfortunately, raw inflation data do not indicate the slope.

I therefore employ a VAR system to estimate the difference between short- and long-run equilibrium accumulative responses of price to input cost shocks. Two reasons justify the adoption of a VAR system. First, with costly price adjustment, the changes in prices follow a serially correlated pattern in response to serially uncorrelated cost shocks. So, a VAR model enables me to trace the dynamics of price response to measure the transitory components in prices that cause earnings to be less persistent. Second, a structure model helps to distinguish between the effects of demand and supply changes, both of which cause optimal prices to change.

For each industry *i* in month *s*, I estimate the following moving average representation of VAR by using monthly data from *s*-60 to *s*. The system has four endogenous variables, with one constant and two lags:

$$y_{is} = \Pi_i^* + \sum_{k=1}^{\infty} \Pi_{ik} \times \varepsilon_{is-k}, \tag{12}$$

where y_{is} is a 4×1 vector of the endogenous variables π_{is}^c, π_{is}^p, the monthly growth rates of the three-month Treasury bill rate ($TB3_s$), and industrial production (IPG_s). I calculate the divergence between the short-run response of price and the long-run equilibrium response caused by a cost shock that hits industry *i* in month *s-k*.[20]

The monthly price divergence for industry *i* as of month *s* is then calculated as

$$\omega_{is} = \sum_{k=0}^{50} [\ \underbrace{(\widehat{\Pi}_{ik}^p) - (\widehat{\Pi}_{ik}^c)}_{Short-run\ Response} \ - \ \underbrace{(\widehat{\Pi}_{i50}^p) - (\widehat{\Pi}_{i50}^c)}_{Long-run\ Response}\ ] \times \hat{\varepsilon}_{is-k}^c, \tag{13}$$

where $\widehat{\Pi}_{ik}^p$ and $\widehat{\Pi}_{ik}^c$ are estimated coefficients as in Eq. (12). $\hat{\varepsilon}_{is-k}^c$ is the estimated residual in the cost equation under a 60-month rolling window VAR model as in Eq. (12). In addition, I use $\widehat{\Pi}_{i50}^p$ and $\widehat{\Pi}_{i50}^c$ as proxies for long-run equilibrium coefficients. (See Fig. 2.) The annualized price divergence is simply the sum of ω_{is} over the past 12 months, which is calculated as

$$\Omega_{is} = \sum_{h=0}^{11} \omega_{is-h}. \tag{14}$$

Ω_{is} measures the extent to which an industry's short-run price in month *s* is temporally distorted by firms' sluggishness in adjusting prices over the past 12 months. Annualizing the monthly price divergence implies that the decision regarding price adjustment depends on the average relative price. It attenuates the concern that the current month price deviates from the long-run equilibrium level simply because of a temporary cost shock. The measured price divergence

[20] For the selection of control variables in VAR, see Fama (1981) and Lee (1992).

shows how much the current price needs to be adjusted to reach the long-run equilibrium level. A positive price divergence implies that a firm has experienced cost decreases and, because of incomplete price adjustment, its current price stays above the equilibrium level. In other words, firms in industries with positive price divergences receive deflation shocks. The same logic applies to a negative price divergence. If adjusting prices is cost-free, then firms should immediately adjust them to eliminate the price divergence.

[Insert Fig. 2 near here]

Table 1 presents the distribution of firm-year observations on the entire regression sample across the two regimes, which are classified based on the sign of estimated price divergence. The number of observations in the two regimes is roughly the same. However, there is heterogeneity in the distributions within each industry. For example, 60.5% of the firm-year observations in oil and gas extraction fall in the negative regime, and 76.2% and 68.4% of observations from the computer and electronic industries, respectively, fall in the positive regime. The cross-industry variation of the distribution reflects the real-world situation. For example, relative to traditional industries, high-technology industries experienced cost reductions due to numerous new inventions over the sample period.

[Insert Table 1 near here]

4.2 Fuzzy regression discontinuity design

There are two empirical concerns. The first concern is that firms' economic performances are noisily measured by accounting earnings. The noise that measures earnings quality is not independent of accounting implementation when cost shock hits. In some extreme cases, the effect of downward nominal price rigidity on earnings property can be fully eliminated by either accrual accounting or earnings manipulation. The second concern is that even though a relationship between nominal price rigidity and earnings persistence is observed in the real data, the correlation may be spurious. Unobservable firm characteristics determining earnings quality can be correlated with the sign or the magnitude of cost inflation.

To address these concerns, an ideal design is to compare earnings quality between firms receiving a small positive cost shock and otherwise identical firms receiving a small negative shock of the same magnitude. I employ a fuzzy regression discontinuity design that takes advantage of a known threshold when determining the probability of a certain group receiving treatment. FDD helps generate randomized variation in other observables (e.g., firm size, leverage, and growth) as long as firms are not able to precisely manipulate the assignment variable near the threshold (Roberts and Whited, 2012). Because the estimated price divergence (the assignment variable) arises as an industry spreads price adjustments over time, a single firm is unlikely to be able to self-select around such a cutoff. The assignment rule in the FDD is

$$0 < \lim_{\Omega\uparrow 0} \Pr(A = 1|\Omega) - \lim_{\Omega\downarrow 0} \Pr(A = 1|\Omega) < 1. \tag{15}$$

The treatment effect is identified as the ratio

$$E(\tilde{\beta}|\Omega) = \frac{\lim\limits_{\Omega\downarrow 0} E(Y|\Omega) - \lim\limits_{\Omega\uparrow 0} E(Y|\Omega)}{\lim\limits_{\Omega\downarrow 0} Pr(A=1|\Omega) - \lim\limits_{\Omega\uparrow 0} Pr(A=1|\Omega)}, \tag{16}$$

where Y is the outcome of interest. If there is a discontinuous jump in the probability of receiving treatment around a cutoff and the assignment error is purely random, I can exploit a rule of thumb that induces exogenous variation in the probability of price adjustment with similar firm characteristics. I can directly use the following equation to estimate the asymmetric effect of price adjustment rigidity on earnings persistence:

$$Y_{it} = \beta_0 + \beta_1\, Downward + \beta_2\, Z_{it} + \varepsilon_{it}, \tag{17}$$

where *Downward* is an indicator equal to one if Ω_{is} is greater than zero and zero otherwise, and Z_{it} is a set of control variables. The magnitude of discontinuity, β_1, is estimated by the difference in these two smoothed functions evaluated at the cutoff range. This coefficient should be interpreted locally in the immediate vicinity of the threshold.[21]

However, if the error of assigning treatment is correlated with earnings persistence (the outcome variable), then a selection bias problem would naturally arise. For this reason, a two-stage least squares (2SLS) procedure is necessary. To perform this, I instrument the probability of price adjustment using *Downward* and then use the fitted value to replace *Downward* in Eq. (17). In unreported tables, results from a 2SLS procedure are similar to results estimated by the methodology used in Eq. (17).[22]

The estimation method is based on a subsample of firm-year observations that are close to the point of discontinuity. I define two discontinuity samples as those firm-year observations for which the absolute values of the estimated price divergences are less than 1% and less than 2%. According to statistics deciding optimal bandwidth, 1% and 2% are about 100% and 200% of the estimated optimal bandwidths, respectively. This restriction reduces the sample size by 35%.

Table 2 reports the summary statistics of firm characteristics on the discontinuity sample. Most of these characteristics bear a known relationship with earnings quality. I define the discontinuity sample as those firm-year observations for which the absolute value of price deviation is less than 0.02. The sample is stratified by whether the estimated price deviation is above or below zero. There is also significant heterogeneity in firm characteristics.

[Insert Table 2 near here]

5. Empirical results

[21] Keys et al. (2010) and Keys et al. (2012) adopt a similar FDD.
[22] For econometrics issues regarding the fuzzy regression discontinuity design, see Imbens and Lemieux (2008) and Roberts and Whited (2012).

5.1 Downward nominal price rigidity

Discontinuity exists in the probability of a price adjustment occurring at monthly frequencies. On each side of ω_{is} = 0, I divide the entire sample (a panel of industry-level data) into 50 equal-size bins and calculate the average value of these probabilities. The indicator *Adjustment* is defined as one if $\pi_{i,s+1}^{p}$ satisfies two criteria: (1) $\pi_{i,s+1}^{p} > 0$ if $\omega_{is} < 0$ or $\pi_{i,s+1}^{p} < 0$ if $\omega_{is} > 0$ and (2) $|\pi_{i,s+1}^{p}| > |\omega_{is}|$ and zero otherwise. The first condition is that $\pi_{i,s+1}^{p}$ goes in the opposite direction of ω_{is}, the monthly price deviation measured in *s*. The second condition is that the magnitude of $\pi_{i,s+1}^{p}$ exceeds that of ω_{is}. These two conditions essentially describe the possibility that a price gap is filled up by a price adjustment. A clear jump in the defined probability of the adjustment is visible in Panel A of Fig. 3, which shows a more than 30% reduction in the average value *Adjustment* as the assignment variable ω_{is} crosses the cutoff from left to right. To verify the role of expected inflation in the asymmetric price adjustment, I measure the monthly rate of expected inflation in input costs as the fitted value of π_{is}^{c} from Eq. (12). Panels B and C of Fig. 3 show that the discontinuity in the probability of price adjustment occurring in month *t* comes only from the subsample in which input cost is expected to inflate.

[Insert Fig. 3 near here]

Table 3 shows the results of the Local Wald estimation, which amounts to estimating a series of liner regressions over a certain bandwidth on both sides of a specified cutoff point. The size of the discontinuous jump, the Local Wald Estimator, is estimated at zero cutoffs of the measured *Price Divergence*. In Panel A, the Local Wald estimators compare the monthly probabilities of price adjustment below and above the threshold of ω_{is}= 0. The dependent variable of the regression is *Adjustment*. Columns (1)–(2) of Panel A show that, when the *Price Divergence* crosses from slightly less to slightly more than zero, the probability of price adjustment at the monthly frequency is reduced by about 40%. To further assess the effect of trend inflation on asymmetric price adjustment, I divide the regression sample into two subsamples based on the sign of expected inflation in input costs. The estimations, reported in Columns (3)–(6) of Panel A, are consistent with the model prediction by Ball and Mankiw (1994) in which firms find adjusting prices downward less worthwhile when expected inflation is positive. In Panel B, I estimate the discontinuous jump in the probability of price adjustment at an annual frequency. To do so, I define a dummy variable as one if *Adjustment* is equal to one for more than six out of the past 12 months and zero otherwise. Panel B presents estimates of the effects of downward nominal price rigidity on the annualized probability of price adjustment. The results are consistent with those reported in Panel A.

[Insert Table 3 near here]

Two limitations of the evidence must be cited. First, price changes in the following months do not necessarily correspond to price divergences. Many other economic forces, such as changes in interest rates, can have confounding effects. Second, Fig. 3 does not reveal how much the downward adjustment is delayed. To overcome these limitations, I adopt a similar approach as Peltzman (2000) to estimate the price response dynamics. I specify another VAR system to compare the magnitude of price adjustment in response to positive versus negative cost shocks. The new VAR system has six endogenous variables at monthly frequencies: prices (π^p), costs (π^c), the three-month T-bill rate ($\Delta TB3$), industrial production growth (ΔIP), positive divergence ($Divergence^+$), and negative divergence ($Divergence^-$). I identify the sign of divergence because an intrinsic difference exists between downward and upward price adjustments. The adjustment speed is measured as the cumulative response of π_{is}^p to $Divergence^+$ or $Divergence^-$ in month k ($0 < k < 50$) as a fraction of the cumulative response in month 50. The value-weighted average of adjustment speed of a representative Compustat firm is calculated based on a 10% random sample drawn from the industry-level VAR estimates. The average is weighted by the frequency with which each industry appears in the entire regression sample.

Panel A of Fig. 4 illustrates the asymmetry in the accumulative response of price to cost shocks over 50 months following inflation and deflation Panel B shows the gap in the responses. The results suggest that, compared with adjustments following cost deflation, adjustments following the same size of cost inflation take place more quickly. The gap peaks at 20%, approximately three months after the origin of cost shocks. This sharp contrast is much attenuated as time passes; that is, the gap disappears after 12 months.

[Insert Fig. 4 near here]

5.2 Earnings persistence

Table 4 presents the estimated effects of downward nominal price rigidity on earnings persistence on discontinuity samples with varying bandwidths over a period of 14 fiscal years, from 1998 through 2011. Fama-MacBeth regressions are performed. The econometric specification in each cross-sectional regression follows the discussion in Subsection 4.2. The main dependent variable is $Earnings_{i,\,t+n}$ (n = 1, 2, 3), defined as EBITDA scaled by sales. The persistence of profit margin measures the extent to which revenues and costs are mismatched due to the downward nominal price rigidity. The regression specification has a set of controls, including four dummy variables indicating whether $SIZE_{it}$ (firm size), MB_{it} (market-to-book ratio), $DCAWC_{it}$ (discretionary working capital accruals), or $EMPG_{it}$ (employee growth rate) is above the sample median in each year and the interaction between each dummy variable with $Earnings_{i,t+n}$.

[Insert Table 4 near here]

Panels A and B of Table 4 present the regression results when 100% and 200% of bandwidths, respectively, are specified. Columns (1)–(3) in each panel reveal that the earnings persistence coefficient of treatment firms is relatively lower than that of control firms. In a three-year time horizon, the treatment firms experienced an approximately 30% reduction in persistence relative to the control firms. In addition, the treatment effect grows progressively larger over time, as more previously delayed price cuts are realized. For example, the treatment effect grows from 3.5% on the one-year-ahead earnings persistence coefficient to 28.8% on the three-year-ahead one.

To assess the role of trend inflation, I form two subsamples based on the sign of the expected inflation in input costs, as measured in Subsection 5.1. Columns (4)–(9) of Panels A and B report the estimation result. In the subsample in which costs are expected to inflate, the treatment effects on earnings persistence are similar to those reported in Columns (1)–(3). For a limited number of observations with expected cost deflation, the coefficient of the interaction term turns out to be insignificant.

One concern with using profit margin as the earnings measure is that an offsetting change could exist in the quantity sold. For example, suppose a negative cost shock occurs and a firm does not cut its price. Although the profit margin on each unit sold clearly increases, the firm likely would lose sales to competitors that do reduce their prices. In other words, the drop in quantity sold may offset the increase in the profit margin such that there is no overall change in the firm's profits. I therefore reexamine the main hypothesis using EBITDA scaled by total assets, a more typical earnings measure, on discontinuity samples with positive expected inflation.

Table 5 presents the regression results. Statistics in Columns (1)–(3) show that, in the second and third years, treatment firms are associated with 12% and 9% declines in *ROA* persistence relative to the control firms, respectively. In Columns (4)–(6), when the bandwidth is widened to 2%, the treatment effect is about 5%–8% and is concentrated in the first two years; in the third year, negative cost shock does not bear any relation with earnings persistence. Overall, the findings in Table 5 suggest that the negative impact of downward price rigidity on earnings persistence is partially offset by an increase in sales after prices are cut. However, the results support the view that price rigidities distort both profit margin and units sold and that such distortions will be corrected after prices are adjusted downward.

[Insert Table 5 near here]

5.3 Earnings smoothing

The analysis so far has focused on how a pricing decision affects the persistence of earnings. To better understand how accounting earnings is affected, I consider whether the results in Table 4 rest more on the contribution of cash flows to or the accruals component of earnings' mean-reversion rate.[23] I disaggregate EBITDA into two components: operating cash flows and working capital accruals. Table 6 presents the regression results when the contributions of operating cash flows and working capital accruals to earnings persistence are separately assessed. Within two years after a cost shock, the treatment rests much more on operating cash flows than on working capital accruals. Not until the third year does the treatment effect on accruals becomes significant and grow to a magnitude comparable with that of cash flows.

[Insert Table 6 near here]

[23] For example, after costs decline, firms write down old inventories with a lag, causing earnings to be less persistent. However, this effect can be offset by firms strategically purchasing a large amount of new inventories at low costs. In this case, the implication of working capital accruals for earnings persistence is more ambiguous than that of operating cash flows.

The results in Table 6 show the role of accounting in mitigating the adverse effect of downward nominal price rigidity on the persistence of operating margins. The findings suggest that, compared with cash flows, the mean-reversion process of earnings due to accruals reversal is much slower in the treatment group. Given that operating margin is a key financial statement item that strongly affects stock prices, when cutting prices is costly, managers likely take advantage of accounting policies to produce the most persistent earnings number possible. In this subsection, I examine whether the downward normal price rigidity influences a firm's accounting choice, e.g., managers smoothing the impact of deflation on earnings persistence over time.

I measure earnings smoothing using the standard deviation of quarterly EBITDA divided by the standard deviation of quarterly operating cash flows. For each firm *i* at the end of quarter *m*, I calculate the extent to which earnings are smoothed using EBITDA and cash flows over the next 12 quarters, including quarter *m*. The measure is similar to Leuz et al. (2003), but it uses quarterly data for the purpose of this study. Heterogeneity in the seasonality of sales might drive the variation of earnings smoothing across different firms. To address this concern, I include firm fixed effects.

Table 7 reports FDD estimates of the effect of deflation on earnings smoothing. To be consistent with the specification in Table 6, I examine the response of earnings smoothing to both cash flows and accruals shocks. The coefficients loaded on operating cash flows have negative significance regardless of the sign of price divergence, suggesting that smoothing after cash flows shocks is not sensitive to deflation. As for the coefficients loaded on working capital accruals, which have a much higher mean-revision rate, the regression results show that earnings are only smoothed when firms experience cost decreases. The statistics documented in Table 7 show that the accruals policy is altered to smooth the impact of deflation on earnings persistence over time.[24] The results give a good explanation of why it is not until after the third year when the contribution of accruals to earnings persistence declines in the treatment sample, a striking fact as reported in Table 6.

[Insert Table 7 near here]

5.4 Analyst forecast errors

Although I have established that the downward nominal price rigidity asymmetrically affects earnings persistence, I do not address the question of whether decision makers' use of accounting information will be affected. If a reduction in earnings persistence, accompanied by changes in accounting policy, is fairly transparent to financial statement users (e.g., analysts and investors), then the quality of accounting earnings will not be impaired (Dechow et al., 2010). However, this is not true in real life. In this subsection, I examine how security analysts make use of accounting information when firms are faced with downward nominal price rigidities. Security analysts frequently use accounting information to make earnings forecasts or to make recommendations to retail investors. If they cannot estimate earnings persistence, a correlation should be evident between earnings surprises and forecast errors following quarterly earnings announcements. I show that analysts overestimate the persistence of earnings surprises in firms receiving input cost deflations during the period in which announced earnings are generated.

Table 8 shows how analysts' estimation of the persistence of earnings surprises differs between the treatment and control groups on the discontinuity sample with 2% bandwidth. The regression results on the discontinuity sample with 1% bandwidth are very similar. I look at the response of forecast errors to earnings news after earnings announcements of quarter *m*. Earnings

[24] When the level of accruals is initially low, its reversal helps earnings. So, managers have fewer incentives to smooth earnings after experiencing negative shock to accruals.

news is measured by the unexpected earnings surprises (*SUE*), which is the difference between the difference between earnings per share (EPS) after extraordinary items in fiscal quarter *m* and *m*-4, scaled by stock price at the end of quarter *m*.[25] Monthly forecast error is defined as the difference between analysts' consensus forecasts for EPS in the current or the following year and the actual EPS. Forecast error is scaled by stock price as of the end of quarter *m*. To see how analysts' estimation of earnings persistence evolves over time, I measure monthly errors from the second to the 12th month after earnings news are released.

[Insert Table 8 near here]

Columns (1)–(6) of Table 8 report the FDD regression results when the one-year-ahead forecast errors are used as an independent variable. The estimation results show that analysts do not overestimate the persistence of earnings news. For example, both *SUE* and *SUE* × *Downward* turn out to be statistically insignificant, despite how many months have elapsed after earnings announcements. The results are consistent with those of Table 4, in which the impact of *Downward* is very negligible on the one-year-ahead earnings persistence coefficient. However, Columns (7)–(12) of Table 8 show a different picture. *SUE* is strongly negative within six months after the announcement and *SUE* × *Downward* is strongly positive within eight months after the announcement. The magnitude of *SUE* × *Downward* is larger than that of *SUE*, suggesting that security analysts overestimate (underestimate) the persistence of earnings news in the treatment (control) group. The estimation results are consistent with earnings persistence declining in the second year, as documented by the estimation results in Table 4 and 5. The results in Table 8 suggest that security analysts do not accurately process earnings information to assess the extent to which earnings shocks will persist into the future. The results imply that,

[25] I also replace *SUE* with the difference between EBITDA/sales in fiscal quarter *m* and *m*-4. The estimation results are similar.

when input cost fluctuates, information asymmetry arises between firms and analysts. Analysts still seem to employ the unconditional persistence coefficient regardless of the sign of inflation. Such a heuristic approach leads to an overestimation (underestimation) of earnings persistence in firms experiencing input cost inflation (deflation).

Two possible mechanisms are driving the observed pattern in Table 8. The first is that, although analysts have access to the same industry-wide inflation data as I do, they have imperfect information about the extent to which each individual firm's earnings will be affected. For example, each firm can negotiate with its suppliers to share losses or profits caused by cost shocks, but the negotiation outcome is not publicly disclosed. When output prices fail to quickly respond to cost deflations, firms' private information about changes in both their input costs and quantities to be sold will not be fully revealed, which exacerbates information asymmetry in the financial market. As a result, analysts cannot perfectly distinguish between transitory earnings (caused by price rigidity) and permanent earnings (caused by other shocks such as favorable shifts in demand). The second is that the market simply does not use the same approach as I do to assess the industry-wide impact of cost inflations on output prices. For example, the market relies on raw inflation data and does not filter out measurement errors.

Analysts are faced with information frictions, implying that their forecasts errors will be both predictable and serially correlated. I draw from two related, existing lines of study to explain why a serial correlation may arise. First, forecast errors can be auto-correlated when analysts are faced with parameter uncertainties about the quarterly earnings process and learn rationally about them over time (e.g., Markov and Tamayo, 2006). In the context of price rigidity, a transitory earnings shock introduces uncertainty about the true earnings persistence coefficient, making learning more difficult. Second, a rise in transitory earnings, about which the market has imperfect information, makes acquiring information more costly for analysts. As such, analysts' production of information becomes rigid, and they simply rely on past information (i.e., released earnings news) to predict future earnings, leaving forecast errors to be serially correlated. For example, Coibion and Gorodnichenko (2012) find evidence consistent with the predictions under information rigidities. That is, inflation or unemployment forecast errors are positively serially correlated in response to a variety of macroeconomic shocks.

5.5 Market reaction to earnings news

In this subsection, I examine whether investors' response to earnings surprises matches with the pattern of analyst forecast errors as documented in Table 8. It is natural to hypothesize that, when investors do not have perfect information, biases in analyst forecasts can influence stock prices. Therefore, the results in Table 8 imply that, when analysts start to adjust their forecasts toward the actual EPS, stock prices in firms experiencing cost deflations will move in the opposite direction as earnings surprises, leading to a negative post-earnings announcement drift.

Table 9 reports the FDD estimates of the treatment effect on the earnings response coefficient (ERC) and the post-earnings announcement drift for firms both with and without analyst coverage. Panels A and B report the results on the pooled sample and the sample with analyst coverage, respectively. To evaluate the impact of analysts' sluggishness in adjusting their forecasts in response to cost deflations, PEAD is calculated using windows with different lengths. Column (1) of both panels reports the effect of downward price rigidity on ERC. The dependent variable is the accumulative, size, and book-to-market adjusted abnormal return in the window of (-1, +1) around the announcement of earnings in quarter *m*. *SUE_Rank* is the ranking of the difference between EPS after extraordinary items in quarter *m* and *m*-4, scaled by stock price at the end of quarter *m*.[26] Rankings are divided by the total number of observations in the same quarter. Surprisingly, no difference exists in the estimated ERC between the two groups. This is roughly consistent with the findings in Column (1) and (7) of Table 8. That is, analysts' one- and two-year-ahead EPS forecasts are not affected within a short window immediately after an earnings announcement.

[Insert Table 9 near here]

Columns (2)–(5) of both panels report the results for PEAD, which is measured as the accumulative, size, and book-to-market adjusted abnormal returns after the announcement of earnings in quarter *m.* The four measures of PEAD are calculated from the second day following the announcement of earnings in quarter *m* to one day before the following announcement (*PEAD1*) and to 180 days (*PEAD2*), 240 days (*PEAD3*), and 300 days (*PEAD4*) after the quarter *m* announcement. In all regression specifications, the interaction terms between *Downward* and *SUE* rankings are significantly negative. In Column (5) of both panels, where PEAD is calculated using the longest window, the magnitude of the negative interaction term outweighs that of *SUE,* implying a negative PEAD for firms receiving negative cost shocks. In addition, firm-quarter observations with analyst coverage experience a much larger negative PEAD, supporting the view that stock returns following earnings announcements are affected by analyst forecasts about the persistence of earnings news. Taken together, the results suggest that, as analysts gradually update their forecasts over time following earnings announcements, the stock market corrects its belief on the persistence of earnings news.

[26] This measure is based on Livnat and Mendenhall (2006) and has the advantage of being able to measure *SUE* for almost every firm-quarter in the Compustat database.

6. Conclusion

Nominal price rigidity is the most central aspect of New Keynesian economics. The school largely relies on the concept of menu costs, the costs of changing nominal prices, to establish that a monetary shock can prevent a market from reaching equilibrium in the short run. Prices have been found to be downward rigid, which in turn affects the aggregate economy asymmetrically. For example, Cover (1992) finds that positive money supply shocks do not have an effect on real GNP, while negative shocks do.

Little is known about the impact of downward nominal price rigidity on firm-level incomes, despite its frequent application in the field of macroeconomics. When deflation shock hits, price rigidity causes a mismatch between a firm's revenues and costs. Such a mismatch declines as prices are adjusted downward in the long run. So, one question naturally arises: Will downward price rigidity impair the quality of accounting earnings?

Viewed as a whole, this paper studies the effect of downward nominal price rigidity on the quality of accounting earnings (measured by operating profit margin) for a majority of US public firms in the period 1998–2011. The key finding of the study is that, over the past two decades, although the annualized inflation rate has been only about 2.5%, firms' reluctance to cut prices reduces earnings persistence by nearly 30% over a three-year horizon. More important, such a reduction in earnings persistence is associated with a deterioration in the quality of accounting earnings. For example, accounting earnings are smoothed to partially mitigate the adverse effect of downward rigidity on earnings persistence, implying that management teams are typically aware of the capital market consequences of a delayed price adjustment. The empirical findings also suggest that the downward nominal price rigidity exacerbates information asymmetry between firms and decision makers (e.g., analysts and investors). For example, analysts are faced with information frictions in understanding the implications of cost deflation for earnings persistence. Their forecast errors are thus predictable and serially correlated, which in turn influences the stock price movements around earnings announcements.

Taken together, the paper offers a better understanding of earnings quality in the context of a moderate inflation environment, in which the role of historical cost accounting is limited. Moreover, the results of the study show that earnings quality can be strongly influenced by product market frictions, i.e., costly price adjustment. Thus, the findings have implications for practitioners, regulators, and researchers. To further assess the importance of this issue to accounting, future research should focus more on the impact of nominal price rigidity on firms' information environment; for example, whether the slowness of price adjustment causes information asymmetry in other dimensions (e.g., debt contracting) and, perhaps equally important, whether firms take into account the informational cost to make operational decisions, i.e., adjusting output prices in response to a variety of shocks.

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Appendix A. Industry classification and source of inflation data

Industry Name	BEA	NAICS	Data Source	Price Code
Farms	111CA	111	Bureau of Labor Statistics, Commodity	WPU01
Forestry, fishing, and related activities	113FF	113	Bureau of Labor Statistics, Industry	PCU1133
Oil and gas extraction	211	211	Bureau of Labor Statistics, Industry	PCU211
Mining, except oil and gas	212	212	Bureau of Labor Statistics, Industry	PCU212
Support activities for mining	213	213	Bureau of Labor Statistics, Industry	PCU213
Utilities	22	22	Bureau of Labor Statistics, Industry	PCU221
Construction	23	23	US Census Bureau Index of New Single-Family Houses Under Construction	
Wood products	321	321	Bureau of Labor Statistics, Industry	PCU321
Nonmetallic mineral products	327	327	Bureau of Labor Statistics, Industry	PCU327
Primary metals	331	331	Bureau of Labor Statistics, Industry	PCU331
Fabricated metal products	332	332	Bureau of Labor Statistics, Industry	PCU332
Machinery	333	333	Bureau of Labor Statistics, Industry	PCU333
Computer and electronic products	334	334	Bureau of Labor Statistics, Industry	PCU334
Electrical equipment, appliances, and components	335	335	Bureau of Labor Statistics, Industry	PCU335
Motor vehicles, bodies and trailers, and parts	3361MV	3361	Bureau of Labor Statistics, Industry	PCU3361–3363
Other transportation equipment	3364OT	3364	Bureau of Labor Statistics, Industry	PCU3364–3369
Furniture and related products	337	337	Bureau of Labor Statistics, Industry	PCU337
Miscellaneous manufacturing	339	339	Bureau of Labor Statistics, Industry	PCU339
Food and beverage and tobacco products	311FT	311	Bureau of Labor Statistics, Industry	PCU311–312
Textile mills and textile product mills	313TT	313	Bureau of Labor Statistics, Industry	PCU313–314
Apparel and leather and allied products	315AL	315	Bureau of Labor Statistics, Industry	PCU315–316
Paper products	322	322	Bureau of Labor Statistics, Industry	PCU322
Printing and related support activities	323	323	Bureau of Labor Statistics, Industry	PCU323
Petroleum and coal products	324	324	Bureau of Labor Statistics, Industry	PCU324
Chemical products	325	325	Bureau of Labor Statistics, Industry	PCU325
Plastics and rubber products	326	326	Bureau of Labor Statistics, Industry	PCU326
Wholesale trade	42	42	Bureau of Labor Statistics, Commodity	WPU00000000
Retail trade	44RT	44	Bureau of Labor Statistics, Consumers	CUSR0000SA0
Air transportation	481	481	Bureau of Labor Statistics, Industry	PCU481
Rail transportation	482	482	Bureau of Labor Statistics, Industry	PCU482
Water transportation	483	483	Bureau of Labor Statistics, Industry	PCU483
Truck transportation	484	484	Bureau of Labor Statistics, Industry	PCU484

Transit and ground passenger transportation	485	485	Bureau of Labor Statistics, Industry	PCU481–484, 486
Pipeline transportation	486	486	Bureau of Labor Statistics, Industry	PCU486
Other transportation and support activities	487OS	487	Bureau of Labor Statistics, Industry	PCU488,492
Warehousing and storage	493	493	Bureau of Labor Statistics, Industry	PCU493
Publishing industries (includes software)	511	511	Bureau of Labor Statistics, Industry	PCU511
Motion picture and sound recording industries	512	512	Bureau of Labor Statistics, Industry	PCU511
Broadcasting and telecommunications	513	515	Bureau of Labor Statistics, Industry	PCU515, 517
Information and data processing services	514	518	Bureau of Labor Statistics, Industry	PCU511
Federal Reserve banks, credit intermediation, and related activities	521CI	521	Federal Reserve Bank of St. Louis	Bank prime loan
Securities, commodity contracts, and investments	523	523	Bureau of Labor Statistics, Current Employment Statistics survey Employment, Hours, and Earnings	CEU5552300008
Insurance carriers and related activities	524	524	Bureau of Labor Statistics, Current Employment Statistics survey Employment, Hours, and Earnings	CEU5552400008
Funds, trusts, and other financial vehicles	525	525	Bureau of Labor Statistics, Current Employment Statistics survey Employment, Hours, and Earnings	CEU5552500001
Real estate	531	531	US Office of Federal Housing Enterprise Oversight US Monthly Housing Index	
Rental and leasing services and lessors of intangible assets	532RL	532	Bureau of Labor Statistics, Industry	PCU532
Legal services	5411	5411	Bureau of Labor Statistics, Current Employment Statistics survey Employment, Hours, and Earnings	CEU6054110008
Computer systems design and related services	5415	5415	Bureau of Labor Statistics, Current Employment Statistics survey Employment, Hours, and Earnings	CEU6054150008
Miscellaneous professional, scientific, and technical services	5412OP	5412OP	Bureau of Labor Statistics, Current Employment Statistics survey Employment, Hours, and Earnings	CEU6054199008
Administrative and support services	561	561	Bureau of Labor Statistics, Current Employment Statistics survey Employment, Hours, and Earnings	CEU6056100008
Waste management and remediation services	562	562	Bureau of Labor Statistics, Current Employment Statistics survey Employment, Hours, and Earnings	CEU6056200008
Educational services	61	61	Bureau of Labor Statistics, Current Employment Statistics survey Employment, Hours, and Earnings	CEU65000000
Ambulatory health care services	621	621	Bureau of Labor Statistics, Current Employment Statistics survey Employment, Hours, and Earnings	CEU6562100008
Hospitals and nursing and residential care facilities	622HO	622	Bureau of Labor Statistics, Industry	PCU622–623
Social assistance	624	624	Bureau of Labor Statistics, Current Employment Statistics survey Employment, Hours, and Earnings	CEU6562400008
Performing arts, spectator sports, museums, and related activities	711AS	711	Bureau of Labor Statistics, Current Employment Statistics survey Employment, Hours, and Earnings	CEU7071100008, 7071211008

Appendix B. Variable definitions

Panel A: Industry-level Variables

Variable	Description
π_{is}^{p}	Growth rate of the Producer Price Index (PPI) of downstream industry *i* as of month *s*.
π_{is}^{c}	Growth rate of input cost for downstream industry *i* as of month *s*, calculated as $\pi_{is}^{c} = \sum_{j=1}^{n} \lambda_{ijs} \pi_{js}^{p}$. λ_{ijs} is the commodity input from upstream industry *j* as a percentage of total industry intermediates that are directly consumed by industry *i* in year *t* in which month *s* occurs. π_{is}^{p} is the growth rate of the PPI of upstream industry *j* as of month *s*.
π_{s}	Growth rate of the aggregated PPI as of month *s*.
$TB3_{s}$	Growth rate of three-month Treasury bill rate as of month *s*.
IPG_{s}	Growth rate of industrial production as of month *s*.
Price Divergence$_s$	Annualized *Price Divergence* calculated as $\Omega_{is} = \sum_{h=0}^{11} \omega_{i,s-h}$, where ω_{is} is monthly *Price Divergence* estimated from $$\omega_{is} = \sum_{k=0}^{50} [\underbrace{(\hat{\Pi}_{ik}^{p}) - (\hat{\Pi}_{ik}^{c})}_{Short-run\ Response} - \underbrace{(\hat{\Pi}_{i50}^{p}) - (\hat{\Pi}_{i50}^{c})}_{Long-run\ Response}] \times \hat{\varepsilon}_{i,s-k}^{c}.$$ All the parameters are obtained from the moving average representation of a 60-month rolling window vector autoregression (VAR) system with four endogenous variables and two lags: $y_{is} = \Pi_i^{*} + \sum_{k=1}^{\infty} \Pi_{ik} \times \varepsilon_{i,s-k}$, where y_{is} is a 4×1 vector of endogenous variables (π_{is}^{p}, π_{is}^{c}, $TB3_s$, and IPG_s). $\hat{\Pi}_{ik}^{p}$ and $\hat{\Pi}_{i50}^{p}$ are coefficients estimated from Eq. (12), where π_{ik}^{p} is the dependent variable. $\hat{\Pi}_{ik}^{c}$, $\hat{\Pi}_{i50}^{c}$, and $\hat{\varepsilon}_{i,s-k}^{c}$ are coefficients estimated from Eq. (12), where π_{is}^{c} is the dependent variable.
Expected Inflation$_s$	Fitted value of π_{is}^{c} in the equation of $y_{is} = \Pi_i^{*} + \sum_{k=1}^{\infty} \Pi_{ik} \times \varepsilon_{i,t-k}$, where y_{is} is a 4×1 vector of endogenous variables (π_{is}^{p}, π_{is}^{c}, $TB3_s$, and IPG_s).
Adjustment$_s$	Dummy variable defined as one if the magnitude of π_{s+1}^{p} satisfies two criteria: (1) $\pi_{s+1}^{p} > 0$ if $\omega_s < 0$ or $\pi_{s+1}^{p} < 0$ if $\omega_s > 0$ and (2) $\lvert \pi_{s+1}^{p} \rvert > \lvert \omega_s \rvert$ and zero otherwise.
Downward$_s$	Dummy variable defined as one if *Price Divergence*$_s$ is positive and zero otherwise.

Panel B: Firm-level variables

Variable	Description
$Earnings_{t+n}$	Operating income before depreciation (EBITDA) scaled by net sales as of fiscal year $t + n$ (n = 0, 1, 2, 3).
$Cash\ Flows_t$	Cash flow from operations scaled by net sales as of fiscal year *t*.
$Size_t$	Logarithm of total assets as of fiscal year *t*.
MB_t	Ratio of market capitalization over book value as of fiscal year *t.*
ΔWC_t	Change in working capital scaled by averaged total assets as defined in Dechow and Dichev (2002) as of fiscal year *t*.
ΔDWC_t	Residual of the regression of ΔWC_t on $CFO_{t\text{-}1}$, CFO_t, and CFO_{t+1} as defined in Dechow and Dichev (2002) as of fiscal year *t. CFO* is cash flows from operations scaled by averaged total assets.
TA_t	Total accruals as defined in Sloan (1996) as of fiscal year *t*.
DTA_t	Discretionary accruals estimated from the Modified Jones Model as defined in Dechow et al. (1995) as of fiscal year *t*.
$\sigma(Earnings)_t$	Standard deviation of *Earnings* as of fiscal year *t* over the most recent five fiscal years.
$\Delta Sales_t$	Growth rate of net sales from fiscal year *t*-1 to *t*.
$\Delta Employment_t$	Growth rate of the total number of employees from fiscal year *t*-1 to *t*.
$\Delta Capex_t$	Growth rate of capital expenditures from fiscal year *t*-1 to *t*.
$R\&D_t$	Research and development expenditures scaled by total assets as of fiscal year *t*.
$Big\ 4_t$	Indicator variable equal to one if a firm's financial statement as of fiscal year *t* is audited by a Big Four auditing company after 2002 or by a "Big Five auditing company prior to 2002 and zero otherwise.
Unqualified	Indicator variable equal to one if audit opinion as of fiscal year *t* is unqualified and zero otherwise.

Fig. 1. Timeline of events

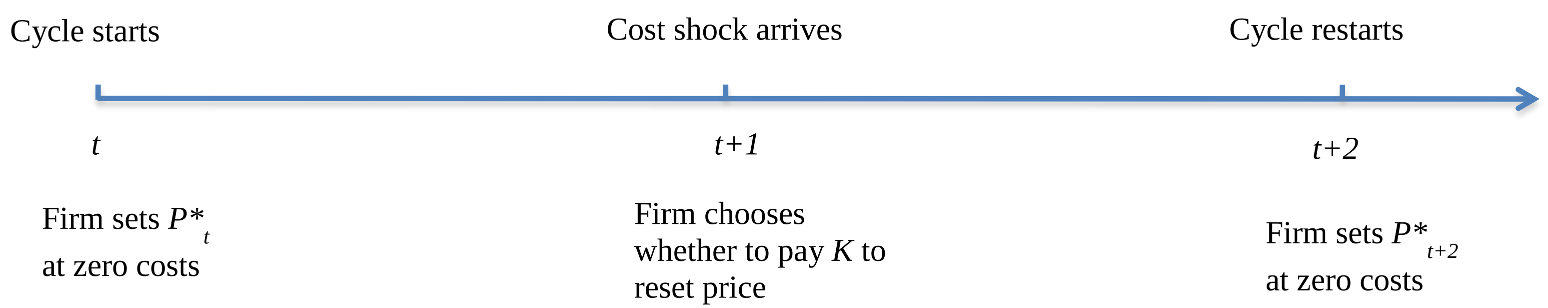


Fig. 2. Distribution of price divergence

This figure shows the distribution of the estimated *Price Divergence*. Industry-year observations with the absolute value of *Price Divergence* above 0.05 are deleted. *Price Divergence* is calculated as $\Omega_{is} = \sum_{h=0}^{11} \omega_{i,s-h}$, where $\omega_{i,s-h}$ is monthly *Price Divergence* estimated within each downstream industry *i*:

$$\omega_{is} = \sum_{k=0}^{50}[\underbrace{(\widehat{\Pi}_{ik}^{p}) - (\widehat{\Pi}_{ik}^{c})}_{Short-run\ Response} - \underbrace{(\widehat{\Pi}_{i50}^{p}) - (\widehat{\Pi}_{i50}^{c})}_{Long-run\ Response}] \times \hat{\varepsilon}_{i,s-k}^{c}\,.$$

All the parameters are obtained from the moving average representation of a 60-month rolling window vector autoregression (VAR) system with four endogenous variables and two lags: $y_{is} = \Pi_i^* + \sum_{k=1}^{\infty} \Pi_{ik} \times \varepsilon_{i,s-k}$, where y_{is} is a 4×1 vector of endogenous variables (π_{is}^{p}, π_{is}^{c}, $TB3_s$, and IPG_s). $\widehat{\Pi}_{ik}^{p}$ and $\widehat{\Pi}_{i50}^{p}$ are coefficients estimated from Eq. (12), where π_{is}^{p} is the dependent variable. $\widehat{\Pi}_{ik}^{c}$, $\widehat{\Pi}_{i50}^{c}$, and $\hat{\varepsilon}_{i,s-k}^{c}$ are coefficients estimated from Eq. (12), where π_{is}^{c} is the dependent variable. Appendix B contains definitions of other variables.

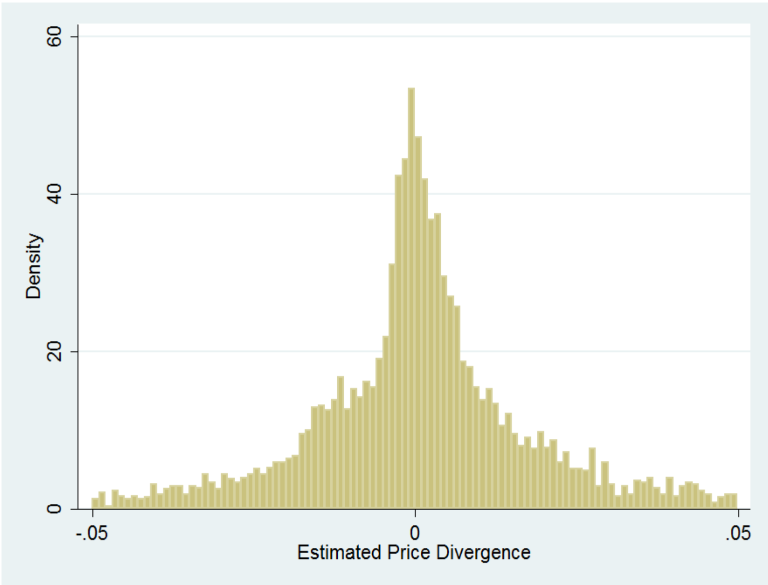
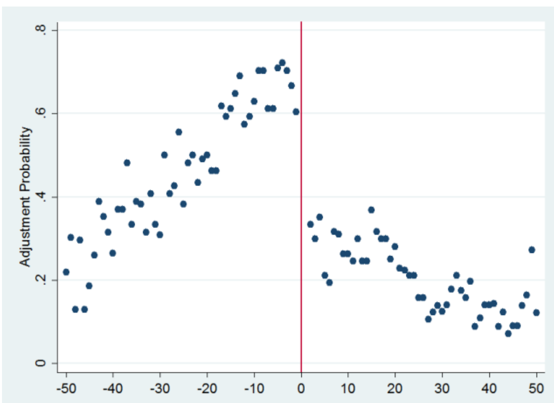


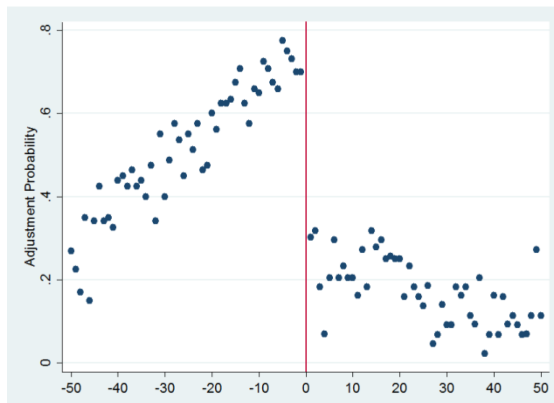
Fig. 3. Discontinuity of price adjustment

This figure shows the distribution of the probability of price adjustment around the cutoff in which the monthly *Price Divergence* = 0. Industry-month observations on either side of the cutoff zero are divided into 50 equal-size bins. Panels A, B, and C show the distributions of the monthly probability of price adjustment in the pooled sample, in the regime with expected inflation, and in the regime with expected deflation, respectively. In each bin, the probability of price adjustment is calculated as the mean of *Adjustment*$_t$. *Adjustment* is a dummy variable defined as one if the magnitude of π^p_{s+1} satisfies two criteria: (1) $\pi^p_{s+1} > 0$ if $\omega_s < 0$ or $\pi^p_{s+1} < 0$ if $\omega_s > 0$ and (2) $|\pi^p_{s+1}| > |\omega_s|$ and zero otherwise. Appendix B contains definitions of other variables.

Panel A: Pooled Sample



Panel B: Expected Inflation > 0



Panel C: Expected Inflation < 0

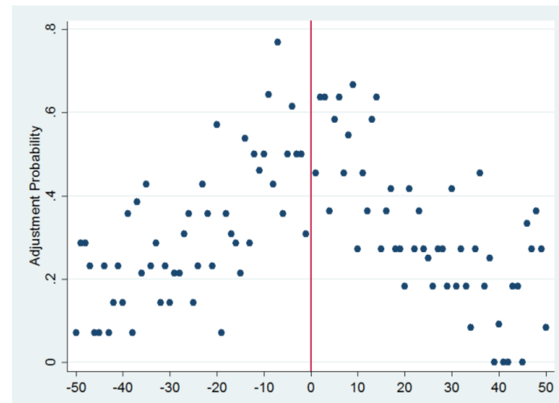
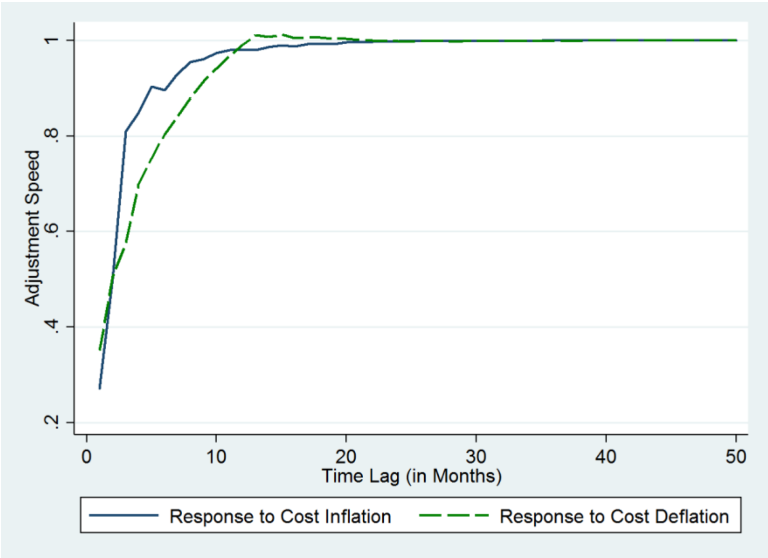


Fig. 4. Asymmetric price adjustment

This figure shows the asymmetry in the speed of price adjustment to reach the long-run equilibrium level. Panel A shows the speeds at which prices are adjusted in response to a positive and a negative shock to *Price Divergence*. Panel B shows the gap between the two speeds. Adjustment speed is measured as the cumulative response of π_s^p to *Divergence*$^+$ *or Divergence*$^-$ in month k ($0 < k < 50$) as a fraction of the cumulative response in month 50. *Divergence*$^+$ is *Divergence* if it is positive; *Divergence*$^-$, if it is negative. In each industry i, a vector autoregression (VAR) system with two lags and six endogenous variables is performed. The endogenous variables are π^p, π^c, $\Delta TB3$, ΔIP, *Divergence*$^+$, and *Divergence*$^-$. The value-weighted average of the adjustment speed of a representative Compustat firm is calculated based on a 10% random sample drawn from the industry-level VAR estimates. The average is weighted by the frequency with which each industry appears in the entire regression sample. See Table 1 for more details about the sample's construction. Appendix B contains definitions of other variables.

Panel A: Adjustment Speed



Panel B: Speed Gap

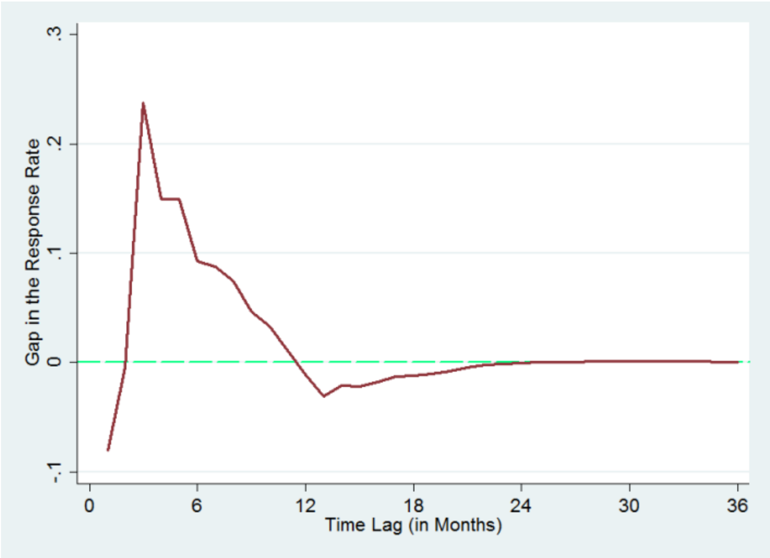
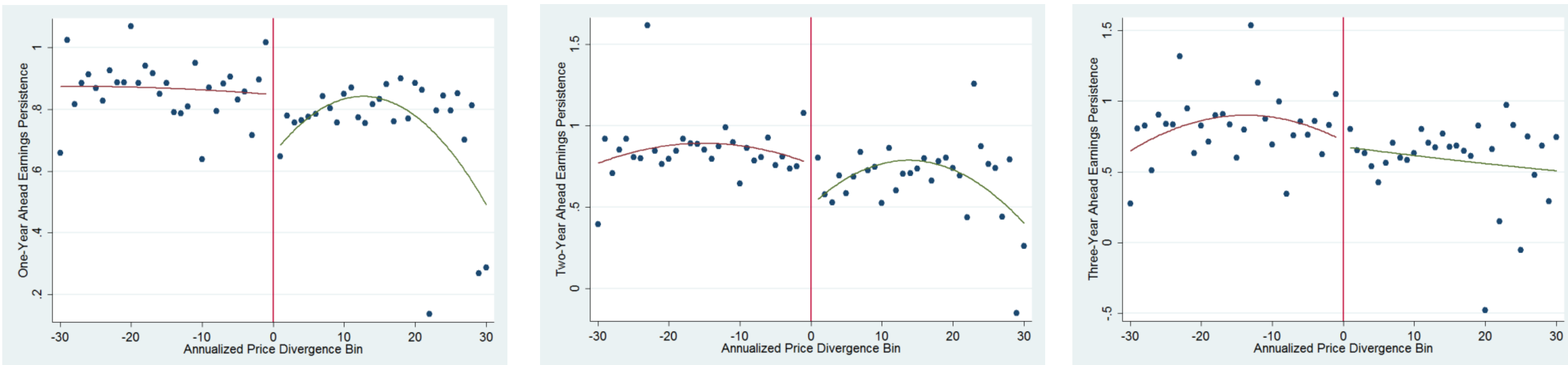


Fig. 5. Distribution of earnings persistence coefficients

This figure shows the distribution of earnings persistence coefficients around the cutoff in which *Price Divergence* = 0. Firm-year observations are based on the entire regression sample. See Table 1 for more details about the sample's construction. Firm-year observations on either side of the cutoff are divided into 30 equal-size bins. The earnings persistence coefficient is the coefficient estimated from the equation: $Earnings_{t+n} = \alpha + \beta Earnings_{t+n} + \varepsilon_t$, n =1, 2, 3. Panel A illustrates the distribution of raw coefficients. Panel B shows the distribution of residual coefficients, which are obtained by regressing the raw coefficients on a variety of median values of variables collapsed within each bin, including $Size_t$, MB_t, ΔWC_t, $\sigma(Earnings)_t$, $\Delta Capex_t$, $\Delta Employment_t$, and $R\&D_t$. Appendix B contains definitions of other variables.

Panel A: Raw Earnings Persistence Coefficients



Panel B: Residual Earnings Persistence Coefficients

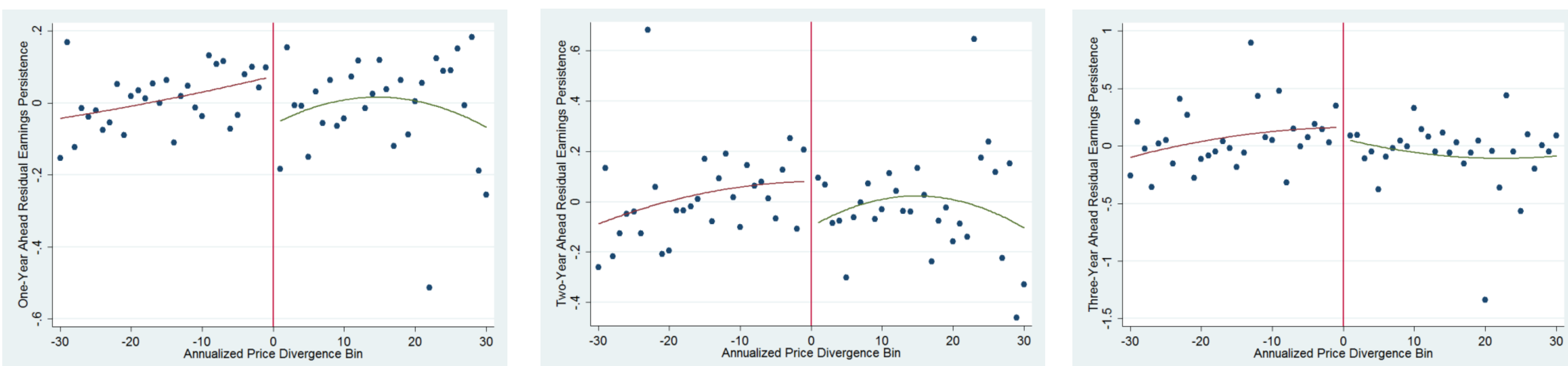


Table 1. Sample construction

Criterion	*N*
Compustat annual industrial sample in the period of 1998–2011	158,380
that belong to the selected industries	76,930
and are US domestic firms	53,685
have non-missing estimated price deviations	49,554
have total assets valued over $1 million	29,147
have positive operating income	26,432
Entire Regression Sample	
have non-missing current and one-year-ahead operating income	21,358
Discontinuity Sample	
have price deviations with less than 2% absolute value	14,343
have non-missing financial variables required as control variables	11,248

Table 2. Firm characteristics across inflation regimes

This table presents a comparison of firm characteristics across the two inflation regimes. Two discontinuity samples are formed based on the sign of *Price Divergence*. *Inflation* refers to firm-year observations in which *Price Divergence* < 0 and |*Price Divergence*| ⩽ 0.02. *Upward* refers to firm-year observations in which *Price Divergence* < 0. *Downward* refers to firm-year observations in which *Price Divergence* > 0. $Earnings_{t+n}$ is operating income before depreciation scaled by net sales as of fiscal year *t*+*n* ($-1 \leq n \leq 3$). *Cash Flows* is cash flows from operations scaled by net sales. *Size* is the logarithm of total assets. *MB* is the ratio of market capitalization over book value. Δ*WC* is the change in working capital as defined in Dechow and Dichev (2002) scaled by total averaged assets. Δ*DWC* is the residual of the regression of Δ*WC* on CFO_{t-1}, CFO_t, and CFO_{t+1}, where *CFO* is cash flows from operations scaled by averaged total assets. *TA* is total accruals. *DTA* is the discretionary accruals estimated by the Modified Johns Model. σ(*Earnings*) is the standard deviation of *Earnings* over the most recent five years. Δ*Sales* is the annual growth rate of net sales. Δ*Employment* is the annual growth rate of total number of employees. Δ*Capex* is the annual growth rate of capital expenditures. *R&D* is expenditures on research and development scaled by total assets. *Big4* is a dummy variable defined as one if the firm is audited by a Big Four auditing company prior to 2002 or by a Big Five auditing company after 2002 and zero otherwise. *Unqualified* is a dummy variable defined as one if the auditor opinion is unqualified and zero otherwise. Appendix B contains definitions of other variables.

Variable	Mean				Median			
	Upward	*Downward*	*Dif*	*t*	*Upward*	*Downward*	*Dif*	*z*
$Earnings_{t-1}$	0.119	0.108	0.010	0.72	0.135	0.123	0.012	8.63
$Earnings_t$	0.159	0.140	0.019	11.31	0.135	0.123	0.012	8.49
$Earnings_{t+1}$	-0.034	-0.048	0.015	0.41	0.132	0.119	0.013	8.56
$Earnings_{t+2}$	-0.105	-0.117	0.012	0.29	0.127	0.116	0.011	7.38
$Earnings_{t+3}$	-0.167	-0.212	0.045	0.89	0.127	0.114	0.013	9.32
$Cash\ Flows_t$	0.112	0.104	0.008	4.32	0.093	0.090	0.003	2.18
$Size_t$	7.008	6.773	0.236	10.21	6.818	6.540	0.278	10.55
MB_t	2.521	2.731	-0.211	-2.46	1.878	2.031	-0.153	-5.33
ΔWC_t	0.018	0.017	0.001	0.88	0.013	0.014	-0.001	-0.38
ΔDWC_t	-0.011	0.056	-0.067	-16.89	-0.004	0.004	-0.008	-9.84
TA_t	-0.008	-0.008	0.000	-0.14	-0.029	-0.026	-0.003	-0.08
DTA_t	-0.005	-0.014	0.010	2.39	-0.008	-0.011	0.003	2.54
$\sigma(Earnings)_t$	0.051	0.049	0.002	0.50	0.023	0.023	0.000	-1.66
$\Delta Sales_t$	0.144	0.126	0.018	2.84	0.080	0.079	0.001	0.33
$\Delta Employment_t$	0.063	0.072	-0.009	-1.79	0.015	0.023	-0.008	-3.21
$\Delta Capex_t$	-0.120	-0.113	-0.007	-0.46	0.064	0.071	-0.007	-0.40
$R\&D_t$	0.050	0.055	-0.005	-2.72	0.019	0.026	-0.007	-7.08
$Big4_t$	0.913	0.912	0.001	0.24	1.000	1.000	0.000	0.24
$Unqualified_t$	0.735	0.757	-0.023	-3.47	1.000	1.000	0.000	-3.47

Table 3. Downward nominal price rigidity:

Local Wald estimation

This table reports the regression results of the local Wald estimation. Panel A presents estimates of the effects of downward nominal price rigidity on the probability of monthly price adjustment. *Adjustment* is a dummy variable defined as one if the magnitude of π_{s+1}^{p} satisfies two criteria: (1) $\pi_{s+1}^{p} > 0$ if $\omega_s < 0$ or $\pi_{s+1}^{p} < 0$ if $\omega_s > 0$ and (2) $|\pi_{s+1}^{p}| > |\omega_s|$ and zero otherwise. Panel B presents estimates of the effects of downward nominal price rigidity on the annualized probability of monthly price adjustment. The dependent variable is a dummy variable defined as one if *Adjustment* equals one for more than six out of the past 12 months and zero otherwise. Expected inflation is measured as the fitted value of π_{is}^{c} in Eq. (12). The standard errors of z statistics are bootstrapped with 200 replications. Appendix B contains definitions of other variables.

Panel A: Probability of Monthly Adjustment

	Pooled		Expected Inflation > 0		Expected Inflation < 0	
	(1)	(2)	(3)	(4)	(5)	(6)
	Coefficient	z	Coefficient	z	Coefficient	z
100% Bandwidth	-0.41	-10.22	-0.51	-11.70	0.02	0.26
50% Bandwidth	-0.39	-10.07	-0.50	-11.57	0.04	0.44
200% Bandwidth	-0.38	-12.60	-0.47	-14.42	0.02	0.41
N	5,452		4,205		1,247	

Panel B: Annualized Probability of Monthly Adjustment

	Pooled		Expected Inflation > 0		Expected Inflation < 0	
	(1)	(2)	(3)	(4)	(5)	(6)
	Coefficient	z	Coefficient	z	Coefficient	z
100% Bandwidth	-0.09	-203.43	-0.13	-3.05	0.10	0.88
50% Bandwidth	-0.09	-574.93	-0.10	-1.59	0.15	1.07
200% Bandwidth	-0.09	-82.16	-0.12	-4.17	0.04	0.43
N	5,235		4,238		533	

Table 4. Downward nominal price rigidity and earnings persistence

This table reports estimates of the effect of downward nominal price rigidity on earnings persistence on discontinuity samples. See Table 1 for more details about the sample's construction. The name of the dependent variable appears at the top of each column. *Downward* is a dummy variable defined as one if *Price Divergence* is greater than zero and zero otherwise. *Expected Inflation* is measured as the fitted value of $\pi_{i,t}^{c}$ in Eq. (12). Panels A and B report the results for 100% (0.01) and 200% (0.02) of bandwidths, respectively. Control variables include (1) four dummy variables defined as one if $Size_t$, MB_t, ΔDWC_t , or $\Delta Employment$ is above the 50th percentile of the sample distribution in each year and zero otherwise and (2) the interaction of each dummy variable in (1) with $Earnings_t$. Fama-MacBeth regressions are performed. The *t*-statistics, in parentheses, are calculated using the standard errors corrected for autocorrelation using the Newey-West procedure. Appendix B contains definitions of other variables.

Panel A: 100% Bandwidth

	Pooled			Expected Inflation > 0			Expected Inflation < 0		
	$Earnings_{t+1}$	$Earnings_{t+2}$	$Earnings_{t+3}$	$Earnings_{t+1}$	$Earnings_{t+2}$	$Earnings_{t+2}$	$Earnings_{t+1}$	$Earnings_{t+2}$	$Earnings_{t+3}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Earnings_t$	0.78	0.84	0.92	0.77	0.88	0.99	0.59	-4.51	0.18
	(15.16)	(16.57)	(4.19)	(13.01)	(18.45)	(4.37)	(3.88)	(-0.97)	(0.64)
$Earnings_t \times Downward_t$	**-0.01**	**-0.11**	**-0.22**	**-0.03**	**-0.12**	**-0.27**	**-0.00**	**-0.37**	**0.03**
	(-0.37)	**(-5.79)**	**(-2.85)**	**(-2.91)**	**(-5.80)**	**(-3.37)**	**(-0.06)**	**(-0.86)**	**(0.34)**
$Downward_t$	-0.00	0.01	0.03	0.00	0.02	0.04	0.01	0.07	-0.01
	(-0.22)	(2.48)	(1.75)	(1.13)	(5.77)	(2.82)	(0.56)	(0.85)	(-0.33)
Intercept	0.01	-0.01	-0.06	0.01	-0.01	-0.07	0.02	0.25	0.06
	(1.60)	(-0.62)	(-1.34)	(1.56)	(-0.90)	(-1.44)	(1.04)	(1.38)	(1.17)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8,556	7,760	6,970	7,044	6,346	5,641	943	902	847
Average R^2	0.68	0.48	0.33	0.68	0.49	0.36	0.82	0.75	0.66

Panel B: 200% Bandwidth

	Pooled			Expected Inflation > 0			Expected Inflation < 0		
	$Earnings_{t+1}$	$Earnings_{t+2}$	$Earnings_{t+3}$	$Earnings_{t+1}$	$Earnings_{t+2}$	$Earnings_{t+3}$	$Earnings_{t+1}$	$Earnings_{t+2}$	$Earnings_{t+3}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Earnings_t$	0.86	0.86	1.04	0.80	0.87	0.92	-6.08	-13.15	0.35
	(25.58)	(23.73)	(8.02)	(12.57)	(25.35)	(6.07)	(-1.14)	(-1.37)	(1.65)
$Earnings_t \times Downward$	**-0.03**	**-0.10**	**-0.30**	**-0.03**	**-0.10**	**-0.15**	**-0.05**	**-0.02**	**-0.03**
	(-2.28)	**(-6.61)**	**(-2.46)**	**(-1.72)**	**(-5.82)**	**(-2.89)**	**(-1.46)**	**(-1.82)**	**(-0.61)**
Downward	0.01	0.01	0.02	0.00	0.02	0.03	-0.24	-0.47	0.01
	(2.00)	(4.26)	(2.14)	(1.44)	(4.66)	(3.32)	(-0.90)	(-1.00)	(1.10)
Intercept	-0.01	-0.01	-0.06	0.01	-0.01	-0.05	0.47	1.01	0.03
	(-1.34)	(-0.84)	(-1.89)	(1.53)	(-0.68)	(-1.44)	(1.17)	(1.43)	(1.51)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11,248	10,069	9,007	9,218	8,175	7,234	1,259	1,198	1,119
Average R^2	0.64	0.47	0.28	0.67	0.49	0.35	0.77	0.82	0.72

Table 5. Downward nominal price rigidity and earnings persistence: An alternative measure

This table reports estimates of the effect of downward nominal price rigidity on an alternative measure of earnings persistence on discontinuity samples. See Table 1 for more details about the sample's construction. The name of the dependent variable appears at the top of each column. *ROA* is operating income before depreciation scaled by total assets as of the beginning of the fiscal year. *Downward* is a dummy variable defined as one if *Price Divergence* is greater than zero and zero otherwise. *Expected Inflation* is measured as the fitted value of π_{is}^{c} in Eq. (12). Panels A and B report the results for 100% (0.01) and 200% (0.02) of bandwidths, respectively. Control variables are (1) four dummy variables defined as one if $Size_t$, MB_t, ΔDWC_t, or $\Delta Employment$ is above the 50th percentile of the sample distribution in each year and zero otherwise and (2) the interaction of each dummy variable in (1) with ROA_t. Fama-MacBeth regressions are performed. The *t*-statistics, in parentheses, are calculated using the standard errors corrected for autocorrelation using the Newey-West procedure. Appendix B contains definitions of other variables.

	ROA_{t+1}	ROA_{t+2}	ROA_{t+3}	ROA_{t+1}	ROA_{t+2}	ROA_{t+3}
	(1)	(2)	(3)	(4)	(5)	(6)
ROA_t	0.77	0.71	0.65	0.77	0.62	0.62
	(15.97)	(51.21)	(12.68)	(23.05)	(16.46)	(10.52)
$ROA_t \times Downward_t$	**-0.03**	**-0.09**	**-0.06**	**-0.05**	**-0.05**	**-0.01**
	(-1.25)	**(-2.87)**	**(-4.23)**	**(-2.21)**	**(-1.81)**	**(-0.25)**
$Downward_t$	0.00	0.01	0.00	0.01	0.01	0.00
	(1.17)	(3.62)	(0.68)	(2.03)	(1.72)	(-0.88)
Intercept	0.02	0.03	0.05	0.02	0.04	0.05
	(2.44)	(5.19)	(4.44)	(3.31)	(5.50)	(5.49)
Bandwidth	0.01	0.01	0.01	0.02	0.02	0.02
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	7,045	6,347	5,642	9,220	8,177	7,234
Average R^2	0.57	0.42	0.32	0.54	0.38	0.30

Table 6. Downward Nominal Price Rigidity and Earnings Persistence: Cash Flows versus Accruals

This table reports estimates of the effect of downward nominal price rigidity on earnings persistence on discontinuity samples with positive *Expected Inflation*. *Expected Inflation* is the fitted value of π_{is}^{c} in Eq. (12). See Table 1 for more details about the sample's construction. The name of the dependent variable appears at the top of each column. *Downward* is a dummy variable defined as one if *Price Divergence* is greater than zero and zero otherwise. ΔWC^{S} is the change in working capital as defined in Dechow and Dichev (2002) scaled by net sales. Control variables include (1) four dummy variables defined as one if *Size*, *MB*, ΔDWC, or $\Delta Employment$ is above the 50th percentile of the sample distribution in each year and zero otherwise and (2) the interaction of each dummy variable in (1) with $Earnings_t$. Fama-MacBeth regressions are performed. The *t*-statistics, in parentheses, are calculated using the standard errors corrected for autocorrelation using the Newey-West procedure. Appendix B contains definitions of other variables.

	$Earnings_{t+1}$	$Earnings_{t+2}$	$Earnings_{t+3}$	$Earnings_{t+1}$	$Earnings_{t+2}$	$Earnings_{t+3}$
	(1)	(2)	(3)	(4)	(5)	(6)
$Cash\ Flows_t$	0.52	0.35	0.07	0.58	0.51	0.26
	(9.99)	(11.31)	(0.45)	(17.58)	(19.03)	(1.68)
$Cash\ Flows_t \times Downward_t$	**-0.08**	**-0.07**	**-0.04**	**-0.11**	**-0.18**	**-0.16**
	(-3.12)	**(-1.82)**	**(-0.95)**	**(-4.65)**	**(-3.79)**	**(-2.60)**
ΔWC_t^S	0.24	0.22	0.52	0.17	0.18	0.30
	(4.36)	(3.77)	(4.94)	(19.87)	(4.91)	(5.41)
$\Delta WC_t^S \times Downward_t$	**-0.03**	**-0.09**	**-0.34**	**0.02**	**-0.07**	**-0.17**
	(-0.48)	**(-2.08)**	**(-2.69)**	**(0.52)**	**(-1.04)**	**(-2.15)**
$Downward_t$	0.01	0.01	0.02	0.01	0.02	0.02
	(2.19)	(4.14)	(2.57)	(2.54)	(2.37)	(3.40)
Intercept	0.04	0.04	0.02	0.04	0.04	0.03
	(11.13)	(6.81)	(0.96)	(12.08)	(16.68)	(2.08)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth	0.01	0.01	0.01	0.02	0.02	0.02
N	7,044	6,346	5,641	9218	8,175	7,234
R^2	0.52	0.38	0.29	0.51	0.38	0.28

Table 7. Downward nominal price rigidity and earnings smoothing

This table reports estimates of the effect of downward nominal price rigidity on earnings smoothing on discontinuity samples with positive *Expected Inflation*. *Expected Inflation* is the fitted value of π_{is}^{c} in Eq. (12). See Table 1 for more details about the sample's construction. The dependent variable is the earnings smoothing measure based on quarterly financial data from quarter *m* to *m+11*. Earnings smoothing is measured as the standard deviation of quarterly *Earnings* over the standard deviation of quarterly *Cash Flows. Downward* is a dummy variable defined as one if *Price Divergence* is greater than zero and zero otherwise. ΔWC^{S} is the change in working capital as defined in Dechow and Dichev (2002) scaled by net sales. *Operating Cycle* is defined as $180 \times (AR_t+AR_{t-1}) / Sales_t + 180 \times (Invt_t+Invt_{t-1}) / COGS_t$. AR_t, $Invt_t$, and $COGS_t$ are account receivables, inventories, and costs of goods sold as of the end of fiscal year *t*. Ordinary least squares regressions are performed. The *t*-statistics, in parentheses, are calculated using the standard errors clustered at the industry-year level. Appendix B contains definitions of other variables.

	Earnings Smoothing	
	(1)	(2)
Cash Flows$_t$	-0.20	-0.19
	(-1.85)	(-2.16)
Cash Flows$_t$ × *Downward*$_t$	**0.06**	**0.05**
	(0.76)	**(0.71)**
ΔWC_t^{S}	0.17	0.12
	(1.72)	(1.66)
ΔWC_t^{S}× *Downward*$_t$	**-0.25**	**-0.23**
	(-2.46)	**(-2.58)**
Downward$_t$	0.00	0.00
	(0.12)	(-0.37)
Size$_t$	0.03	0.04
	(1.74)	(2.61)
MB$_t$	0.00	0.00
	(-0.55)	(-0.58)
Δ*Employment*$_t$	-0.01	-0.01
	(-0.55)	(-0.52)
DTA$_t$	(0.01)	0.00
	(0.27)	(0.01)
σ*(Earnings)*$_t$	0.15	0.07
	(1.08)	(0.49)
Operating Cycle$_t$	0.00	0.00
	(0.91)	(1.12)
Intercept	0.15	0.15
	(1.25)	(1.55)
Bandwidth	0.01	0.02
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
N	5,609	7,309
Adj. R^2	0.51	0.513

Table 8. Downward nominal price rigidity and analysts' estimation of earnings persistence

This table reports estimates of the effect of downward nominal price rigidity on analysts' estimation of the persistence of earnings news on discontinuity samples with positive *Expected Inflation*. *Expected Inflation* is the fitted value of π^{c}_{is} in Eq. (12). The name of the dependent variable appears at the top of each column. $FE1_{m+k}$ and $FE2_{m+k}$ (k = 2, 4, 6, 8, 10, 12) are analyst one- and two-year-ahead forecast errors k months following the announcement of earnings as of fiscal quarter m. Monthly forecast error is the difference between the mean of forecasted earnings per share (EPS) and actual EPS, scaled by stock price at the end of quarter m. *SUE* is the difference between EPS after extraordinary items in quarter m and m-4, scaled by stock price at the end of quarter m. *Downward* is a dummy variable defined as one if *Price Divergence* is greater than zero and zero otherwise. *Return* is the buy-and-hold stock returns over the past 12 months. *BM* is the book-to-market ratio as of the beginning of the fiscal year. *Ln (# of estimates)* is the logarithm of the number of earnings forecasts made in a month. See Table 1 for more details about the sample's construction. Ordinary least squares regressions are performed. The *t*-statistics, in parentheses, are calculated using the standard errors clustered at the firm level. Appendix B contains definitions of other variables.

	$FE1_{m+2}$	$FE1_{m+4}$	$FE1_{m+6}$	$FE1_{m+8}$	$FE1_{m+10}$	$FE1_{m+12}$	$FE2_{m+2}$	$FE2_{m+4}$	$FE2_{m+6}$	$FE2_{m+8}$	$FE2_{m+10}$	$FE2_{m+12}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SUE_m	-0.08	-0.08	-0.04	-0.12	-0.03	-0.08	-0.09	-0.09	-0.08	-0.05	-0.04	-0.01
	(-1.10)	(-1.03)	(-0.55)	(-1.74)	(-0.46)	(-0.29)	(-1.38)	(-1.65)	(-1.65)	(-1.12)	(-1.14)	(-0.38)
$SUE_m \times Downward_m$	**-0.02**	**0.02**	**-0.02**	**0.08**	**-0.13**	**0.07**	**0.11**	**0.14**	**0.12**	**0.10**	**0.05**	**0.06**
	(-0.26)	**(0.20)**	**(-0.23)**	**(0.92)**	**(-1.08)**	**(0.17)**	**(1.41)**	**(2.17)**	**(1.96)**	**(1.84)**	**(1.10)**	**(1.38)**
$Downward_m$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(-1.14)	(-1.44)	(-1.91)	(-1.92)	(-0.49)	(0.52)	(-1.72)	(-1.93)	(-1.56)	(-0.63)	(0.80)	(0.83)
$Return_m$	-0.01	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00
	(-5.27)	(-2.52)	(-2.24)	(-1.01)	(-0.25)	(0.16)	(-3.41)	(-1.45)	(-0.07)	(0.49)	(0.80)	(-0.00)
BM_m	0.01	0.01	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01	0.00	0.00	0.00
	(1.90)	(1.59)	(1.20)	(0.87)	(0.38)	(0.01)	(-1.70)	(-1.52)	(-1.44)	(-1.02)	(-0.78)	(-0.07)
Ln (# of estimates$_m$)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(-0.89)	(-1.18)	(-0.77)	(-0.56)	(-1.22)	(-0.23)	(0.33)	(-0.47)	(-0.55)	(-0.67)	(-0.67)	(-0.80)
Intercept	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00
	(1.41)	(1.74)	(1.75)	(1.41)	(1.66)	(0.30)	(0.91)	(0.79)	(0.69)	(1.67)	(-0.04)	(-0.33)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
N	30,538	22,521	19,985	12,417	5,469	691	32,548	32,465	32,427	32,390	32,286	31,819
Adj. R^2	0.40	0.40	0.36	0.47	0.39	0.90	0.54	0.52	0.50	0.46	0.46	0.41

Table 9. Downward nominal price rigidity and stock market reaction to earnings news

This table reports estimates of the effect of downward nominal price rigidity on stock market reaction to earnings news on discontinuity samples with positive *Expected Inflation*. *Expected Inflation* is the fitted value of π_{is}^{c} in Eq. (12). Panel A reports the estimation results on the pooled sample. Panel B reports the estimation results on the sample with analyst coverage. The name of the dependent variable appears at the top of each column. *CAR (-1, +1)* is the accumulative size, and book-to-market adjusted abnormal return one day before and one day after the announcement of earnings in quarter *m*. *PEAD1* is the accumulative, size, and book-to-market adjusted abnormal return from two days after the announcement of earnings in quarter *m* through one day before the announcement of earnings in quarter *m*+1. *PEAD2*, *PEAD3*, and *PEAD4* are the accumulative, size, and book-to-market adjusted abnormal returns from two days to 180 days, 240 days, and 300 days after the announcement of earnings in quarter *m*, respectively. *SUE_Rank* is the ranking of *SUE* in each fiscal quarter, scaled by the total number of observations in the same quarter. *SUE* is the difference between earnings per share after extraordinary items in quarter *m* and *m*-4, scaled by stock price at the end of quarter *m*. *Downward* is a dummy variable defined as one if *Price Divergence* is greater than zero and zero otherwise. See Table 1 for more details about the sample's construction. Ordinary least squares regressions are performed. The *t*-statistics, in parentheses, are calculated using the standard errors clustered at the fiscal quarter level. Appendix B contains definitions of other variables.

Panel A: Pooled sample

	CAR (-1,+1)	*PEAD1*	*PEAD2*	*PEAD3*	*PEAD4*
	(1)	(2)	(3)	(4)	(5)
SUE_Rank$_m$	0.06	0.05	0.05	0.04	0.04
	(17.43)	(7.86)	(4.87)	(3.82)	(3.67)
SUE_Rank$_m$ × *Downward$_m$*	**-0.00**	**-0.03**	**-0.04**	**-0.04**	**-0.06**
	(-0.76)	**(-3.55)**	**(-3.31)**	**(-3.25)**	**(-3.90)**
Downward$_m$	0.00	0.01	0.02	0.02	0.03
	(0.85)	(2.15)	(2.11)	(2.71)	(3.08)
Ln (# of estimates$_m$)	0.00	0.00	0.00	0.00	0.00
	(-1.45)	(-0.28)	(-0.46)	(-0.11)	(-0.24)
Intercept	-0.02	-0.02	-0.02	-0.03	-0.02
	(-13.13)	(-6.62)	(-4.17)	(-3.60)	(-2.51)
Quarter	Yes	Yes	Yes	Yes	Yes
Bandwidth	0.02	0.02	0.02	0.02	0.02
N	41,953	41,953	41,953	41,953	41,953
Adj. R^2	0.029	0.009	0.012	0.015	0.013

Panel B: Firms with analyst coverage

	CAR (-1, +1)	*PEAD1*	*PEAD2*	*PEAD3*	*PEAD4*
	(1)	(2)	(3)	(4)	(5)
SUE_Rank$_m$	0.05	0.03	0.02	0.01	0.01
	(15.02)	(4.68)	(2.13)	(0.85)	(0.40)
SUE_Rank$_m$ × *Downward$_m$*	**-0.00**	**-0.03**	**-0.04**	**-0.03**	**-0.04**
	(-0.67)	**(-2.76)**	**(-2.77)**	**(-2.06)**	**(-2.62)**
Downward$_m$	0.00	0.01	0.01	0.01	0.02
	(0.49)	(1.64)	(1.59)	(1.55)	(1.78)
Ln (# of estimates$_m$)	0.00	0.00	0.00	0.00	0.00
	(-2.12)	(0.34)	(0.21)	(0.44)	(-0.03)
Intercept	-0.02	-0.02	-0.01	-0.01	0.00
	(-10.07)	(-4.54)	(-2.21)	(-1.35)	(0.21)
Quarter	Yes	Yes	Yes	Yes	Yes
Bandwidth	0.02	0.02	0.02	0.02	0.02
N	34,858	34,858	34,858	34,858	34,858
Adj. R^2	0.024	0.008	0.012	0.014	0.013