Does the stock market make firms more productive?

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Abstract

Management, directly or indirectly, learns from its firm's stock price, so a more informative stock price should make the firm more productive. We show that stock price informativeness increases firm productivity. We provide direct evidence of one channel through which stock price informativeness affects productivity; specifically, we find that CEO turnover is less sensitive to Tobin's q when informativeness is lower. We predict and confirm that the productivity of smaller and younger firms, better governed firms, more specialized firms, and firms with more competition is more strongly related to the informativeness of their stock price. We further address endogeneity concerns with the use of brokerage closures, S&P 500 additions, and mutual fund redemptions as plausibly exogenous events.

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1. Introduction

One important role of the stock market is to provide price discovery (e.g., Bond, Edmans, and Goldstein, 2012; Fama and Miller, 1972; Subrahmanyam and Titman, 1999; Dow and Gorton, 1997; Dow and Rahi, 2003). Investors and managers learn from stock prices. It is well established that the quality of price discovery varies across stocks and stock markets (see, for instance, Morck, Yeung, and Yu, 2013). In this paper, we use differences in the quality of price discovery across US firms to investigate whether better price discovery makes firms more productive and whether it does so differentially across firms. After demonstrating that better stock market price discovery makes firms more productive, we show that the relation between the quality of stock price discovery and productivity varies across firms in predictable ways.

Consider two firms. One firm's stock moves exactly with the market, so no firm-specific information is incorporated in the price. The other firm's stock price incorporates a large amount of firm-specific information. With the first stock, management and investors learn nothing from price moves that they would not learn by looking at a market index. In the other case, the stock price has information about the firm that is separate from information about the market. Some of that information results from trading by investors (e.g., Grossman and Stiglitz, 1980; Glosten and Milgrom, 1985; Kyle, 1985). The contention and evidence in the literature is that this information is valuable to management and investors in guiding their actions. In the case of the first firm, a drop in the stock price is not informative about firm-specific developments; in the case of the second firm, it is.

Once private information is in the stock price, it informs the actions of managers and investors in many ways. For example, corporate managers can learn from the information in stock prices for mergers & acquisitions (M&A) decisions: if a firm's stock price drops after an M&A announcement, the manager may cancel the planned acquisition (Luo, 2005), the acquirer may itself be taken over (Mitchell and Lehn, 1990), or the CEO may lose her job (Lehn and Zhao, 2006). In addition to management, directors and activists can take actions to force changes in how firms are managed, and investors in general can take market-based corrective actions (Bond, Goldstein, and Prescott, 2010). Further,

managerial incentives typically depend directly on stock prices. Bond, Edmans, and Goldstein (2012) review the theoretical and empirical literature on the real effects of price discovery.

There is considerable variation in productivity across firms. Syverson (2004) finds that, within an industry, a plant at the 90th percentile of the total factor productivity (TFP) distribution produces almost twice as much as a plant at the 10th percentile of the TFP distribution with the same inputs. Considerable research effort has been devoted to try to explain this cross-sectional variation, but this research effort has not examined how productivity is affected by price discovery in the stock market. A growing literature examines how the quality of stock price discovery affects firm policies. Perhaps the best known results concern the relation between investment efficiency and price discovery (e.g., Durnev, Morck, and Yeung, 2004; Chen, Goldstein, and Jiang, 2007; Bakke and Whited, 2010; Edmans, Jayaraman, and Schneemeier, 2017). We call this channel the investment channel of informativeness. Since productivity measures take inputs as given, there is no necessary relation between investment decisions that affect firm inputs and firm productivity. For instance, a firm that invests more could simply scale its operations with no changes in productivity.

We find evidence that greater investment efficiency resulting from greater price discovery impacts firm productivity positively, but the investment channel explains only a small fraction of the impact of informativeness on productivity. We also provide direct evidence that price discovery affects productivity through other channels than investment. In particular, we show that CEO turnover is more sensitive to firm value in firms with more informative stock prices. In addition, we find that firms with more informative stock prices have higher revenues, lower operating costs (SG&A), and lower labor expenses.

The extent to which trading incorporates private information in stock prices is measured in the literature by a stock's price informativeness (SPI). Throughout the paper, we highlight results using the two measures of SPI that are most widely used in the literature, the probability of informed trading (PIN) and stock price nonsynchronicity (PSI), but we also establish that our results hold for other measures. PIN measures the probability of informed trading in a stock (Easley, Hvidkjaer, and O'Hara, 2002). This measure has a micro foundation, as it is based on a structural market microstructure model. PSI measures firm-specific return variation. Initiated by Roll (1988), the logic of this measure is to filter

out the market and industry-related components from stock returns. As a firm's idiosyncratic variation increases, the stock price reflects more private information (e.g., Morck, Yeung, and Yu, 2000; Durnev, Morck, and Yeung, 2004).

We use TFP as our main measure of productivity. TFP measures the overall effectiveness and efficiency with which capital and labor are used in the production process. Keeping capital and labor inputs fixed, a firm with higher TFP produces more. To measure TFP at the firm level, we have to estimate a production function with data available from Compustat. To do so, we follow Ackerberg, Caves, and Frazer (2015). Many results in the productivity literature are insensitive to measurement choices (Syverson, 2011), but nevertheless we also use another TFP measure from Chun, Kim, and Morck (2011) and other measures of firm efficiency from the corporate finance literature. We show that these measures are positively related with SPI as well.

Our evidence that firms with better price discovery in the stock market are more productive could be explained by factors that influence both price discovery and firm productivity. For example, one potential omitted factor could be technology shocks, which may lead to higher price informativeness and higher productivity (Chun et al., 2008; Chun, Kim, and Morck, 2011). To make a causal interpretation of our results plausible, we address potential endogeneity concerns in multiple ways. First, we provide difference-in-differences (DiD) estimations using quasi-natural experiments of shocks to SPI. The first experiment involves closures of brokerage research departments, and the second experiment uses additions to the S&P 500 index. Second, we use mutual fund flow pressure as an exogenous shock to price informativeness and show that a decrease in price informativeness leads to lower productivity. Third, we control for firm fixed effects to minimize the possibility that time-invariant firm-specific omitted variables are affecting our results. Fourth, we use a moving average of SPI over the previous three years, which helps alleviate simultaneity and reverse causality concerns. Our results are robust to these approaches to address endogeneity concerns and hence provide strong support for the existence of a causal effect of SPI on TFP.

To investigate the mechanism through which price informativeness affects productivity, we use mutual fund redemptions and brokerage house closures as exogenous shocks to stock price informativeness and study its effects on the sensitivity of CEO turnover decisions to Tobin's q. Mutual

fund redemptions bring downward pressure to the price of affected stocks and have little to do with firm fundamentals (Coval and Stafford, 2007; Edmans, Goldstein, and Jiang, 2012; Dessaint et al., 2019). This fits well with the intuition that price becomes less informative because the variation in stock price does not reveal information on firm fundamentals. More specifically, these fund flow events increase the fraction of noise trading driven by liquidity reasons (funds' fire sales), and they can discourage investors from collecting information on firm fundamentals because information collection is costly but less likely to be used for trading when the stock price is mainly driven by non-fundamental factors.

We find that, after a firm experiences mutual fund flow pressure, its CEO turnover decision is less sensitive to Tobin's q (i.e., less sensitive to market valuation). When the stock price becomes less informative due to the fund flow pressure, we would expect the firm's board to put less weight on firm value when evaluating the CEO. If a CEO's bad performance is disguised by fund flow pressure, keeping the incumbent CEO in the position has negative effects on firm productivity. Similarly, the tests based on brokerage house closures also show that a decrease in price informativeness has a negative effect on the turnover sensitivity to q. These results illustrate one concrete channel through which stock price informativeness affects firm productivity.

We expect the strength of the relation between SPI and TFP to vary depending on firm characteristics. First, the relation should be weaker for larger firms. Holmstrom (1989) argues that larger firms are more bureaucratic, which increases adjustment costs for these firms. We find that the relation between SPI and TFP is weaker but still holds for larger firms. Second, we expect older firms to adjust more slowly as well, as they have developed more formal processes to manage their operations and are more hierarchical (Loderer, Stulz, and Waelchli, 2016). We hypothesize that it is more difficult for investors and managers to extract information from the stock price of more complex firms. Evidence supporting this hypothesis is, for instance, that analyst forecast errors fall as firms become more focused (Gilson et al., 2001). Using firm-level diversification as an index of complexity, we find that the impact of SPI on TFP is weaker for diversified firms. Firms with riskier businesses are less certain about their internal information, and therefore their decisions should rely relatively more on the information in their stock price. Our results pertaining to business risk support this prediction.

Economic theory suggests that the incentives of firms to use stock price information depend on their financial situation and on the environment they are in. Financially constrained firms have strong incentives to allocate resources efficiently to relax their financial constraints, but these constraints may prevent them from implementing changes that require funding. Consequently, whether financially constrained firms make more use of stock price discovery is an empirical matter. We find that the impact of SPI on TFP is stronger for financially constrained firms for some specifications and is never weaker. Firms that operate in a more competitive environment have stronger incentives to make the best use of their resources, as they operate with little slack (e.g., Hart, 1983). We find that the impact of SPI on TFP is stronger for such firms. Lastly, better corporate governance should provide stronger incentives for management to operate the firm more efficiently, so the impact of SPI on TFP should be stronger for firms that have better governance. Our evidence is supportive of that prediction.

Our contributions are as follows. First, the paper adds to the literature on corporate productivity. We provide evidence that stock price informativeness has a positive effect on firms' TFP. Second, we show that the impact of SPI on TFP depends on firm characteristics. We find that the impact falls with firm size, age, and complexity; it increases with competition, financial constraints, and governance. Third, our paper adds to the literature on the effect of financial markets on the real economy. There is a large literature on whether the stock market is a sideshow. The results of this literature are mixed. For instance, David, Hopenhayn, and Venkateswaran (2016) recently conclude from a calibration exercise that learning from financial markets contributes little to aggregate resource allocation. Fourth, our paper contributes to the literature that assesses the benefits and costs of exchange listings for corporations. Our findings are consistent with a role of the stock market in providing information to investors and managers that helps make firms more productive. Importantly, the role we show the stock market playing does not rely on the stock market being a net provider of funds to the corporate sector or funding new firms.

Section 2 reviews the related literature and motivates our tests. Section 3 introduces the measures of stock price informativeness. Section 4 describes the data sources and the sample. Section 5 provides our evidence on the impact of SPI on TFP and addresses potential endogeneity concerns. Section 6 shows the channels through which SPI impacts productivity. Section 7 investigates the cross-sectional

variation in the impact of SPI on TFP. Section 8 provides evidence that SPI affects other measures of firm efficiency. Section 9 concludes.

2. Literature review and hypothesis development

In this section, we first review the literature on the real effects of financial markets and then briefly motivate our empirical tests in light of the literature.

2.1. Review of existing literature

There has been a noticeable increase in the attention paid by research in financial economics on the real effects of financial markets on the economy. Bond, Edmans, and Goldstein (2012) review the literature on the real effects of price discovery. They argue that financial markets have real effects because they affect the actions of decision-makers in the economy, and such effects originate from the informational role of prices. Morck, Yeung, and Yu (2013) provide a summary of the research on the effects of firm-specific information in stock prices on the efficiency of the economy. Wurgler (2000) finds that firm-specific information in stock prices is positively correlated with the country-level efficiency of capital allocation. Morck, Yeung, and Yu (2000) show that firm-specific return variation differs across countries and it is higher in developed markets than in emerging markets. Bai, Philippon, and Savov (2016) conclude that stock price informativeness has increased in the US since 1960. Fernandes and Ferreira (2009) find enforcement of insider trading laws improves price informativeness in developed countries.

The idea that price has an informational role can be traced back to Hayek (1945), who argues that prices can efficiently summarize useful knowledge and spread information through society. Fama and Miller (1972) argue that market prices of securities provide signals for resource allocation, and firms can use them to make production-investment decisions. Dow and Gorton (1997) study the link between stock price informational efficiency and economic efficiency through a theoretical model in which managers can learn from stock prices to make better investments. Their model has two equilibria. In one equilibrium, the information in stock prices guides investment decisions, but in the other

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equilibrium it does not. Bond, Goldstein, and Prescott (2010) provide a theoretical model that shows economic agents take corrective actions based on the information in market prices of a firm's securities.

There is also empirical evidence showing that price discovery in the stock market affects firms' decisions. One branch of the research focuses on the effects of stock price informativeness on firms' investment efficiency. Durnev, Morck, and Yeung (2004) show that more informative stock prices facilitate more efficient investment. Chen, Goldstein, and Jiang (2007) show that the sensitivity of investment to price (or Tobin's q) is stronger when firms' stock price is more informative. Bakke and Whited (2010) also provide evidence that managers learn from stock prices when making investment decisions. Foucault and Frésard (2012) show that cross-listing a stock increases the firm's sensitivity of investment to price. Edmans, Jayaraman, and Schneemeier (2017) carry out an international study in which they use the enforcement of insider trading laws as an exogenous shock to price informativeness and find enforcement increases investment-q sensitivity. Foucault and Frésard (2014) find that a firm's stock price informativeness can have a spillover effect on its rivals' investment decisions.

Existing studies also investigate how stock price discovery affects other corporate decisions besides investment. Subrahmanyam and Titman (1999) theoretically study the relation between stock price efficiency and firms' going-public decisions. Luo (2005) finds that firms learn from market reactions to M&A announcements and what they learn affects their decision of whether to complete M&A deals. Jin and Myers (2006) show that lower price informativeness shifts firm-specific risk to managers and firms with a less informative stock price are more likely to experience large negative returns. Ferreira and Laux (2007) find that firm-specific return variation is positively correlated with corporate governance quality. Gorton, Huang, and Kang (2017) provide evidence that the board's monitoring effort has a negative effect on information production. Ferreira, Ferreira, and Raposo (2011) find a negative relation between price informativeness and board independence. Frésard (2012) shows that stock price informativeness increases the sensitivity of cash saving to Tobin's q. De Cesari and Huang-Meier (2015) demonstrate that price informativeness increases the sensitivity of dividend changes to past stock returns. Ben-Nasr and Alshwer (2016) find that stock price informativeness increases labor investment efficiency.

Although there is research about the effects of price informativeness on different individual corporate decisions, there is no direct evidence on whether higher price informativeness improves firms' productivity. Such evidence is important for our understanding of the real effects of financial markets. One might think that if price informativeness improves the efficiency of some specific firm decisions, it also improves firms' productivity. This may not be the case. For example, if a manager learns from its stock price that there is a larger demand for her firm's products, she then invests more so that she can produce more goods. However, an investment increase may decrease productivity, leave it unchanged, or increase it depending on the nature of the investment and of the production function of the firm. In fact, there is no empirical study that provides direct evidence on the impact of price discovery on productivity. The only work we are aware of that bears on this issue is a calibration exercise in David, Hopenhayn, and Venkateswaran (2016) that is focused on investment and concludes that learning from financial markets contributes little to productivity. Our paper provides direct evidence that price discovery in the stock market improves firm's productivity.

There are different measures for the informativeness of stock prices in the literature. Morck, Yeung, and Yu (2000) propose a measure using firm-specific return variation based on R^2 (Roll, 1988). Easley et al. (1996) and Easley, Hvidkjaer, and O'Hara (2002) develop a measure for the probability of informed trading (PIN). These measures have been widely used in studies of the impact of stock price informativeness. Llorente, Michaely, and Wang (2002) construct a measure for the amount of trading-based information in stock prices called Gamma. Duarte and Young (2009) refine PIN by removing the liquidity component of PIN so that only the portion related to asymmetric information remains.

TFP is the most widely used measure for productivity. It measures the portion of output that is not explained by inputs of capital and labor. Some research uses plant-level data to calculate the corresponding TFP (e.g., Maksimovic and Phillips, 2002; Giroud and Mueller, 2015). This plant-level TFP makes it possible to study the productivity of different plants within a firm. However, our research question is to study how stock price informativeness affects productivity, and individual plants do not have their own stocks. Imrohoroğlu, and Tüzel (2014) use a firm-level TFP to study the link between firm-level productivity and stock returns. We use a firm-level TFP calculated using a more recent method by Ackerberg, Caves, and Frazer (2015).

2.2. Theoretical motivation for our tests

With q theory, investment is related to Tobin's q, which depends on the stock price. Hence, there is a direct relation between the stock price and investment. The motivation for tests that assess the impact of informativeness on investment decisions is that managers put more weight on the stock price in their decisions when the stock price incorporates more firm-specific information. More generally, however, when management, the board, or investors are imperfectly informed when taking decisions, they will use a firm's stock price if the stock price is a signal that is correlated with the value to them of taking a decision. In a Bayesian framework, the weight economic agents put on the stock price when a decision is taken depends on how informative the stock price is. Hence, if the stock price is not informative, they will ignore it, but if it is informative, it will affect their decision as long as the stock price is a useful signal for that decision.

Note that even if managers do not take into account the stock price directly, they may take it into account indirectly because it influences the board or other shareholders. It follows that stock price changes can have a direct impact on managerial decisions because management pays attention to stock prices, or an indirect impact because stock prices affect the actions of shareholders and the board. We would expect the impact to increase with the extent to which the stock price has information that managers would not have otherwise, which means that the impact increases with the informativeness of the stock price.

There are countless decisions that are made concerning a firm that are potentially affected by the stock price. For instance, firm decisions to issue securities depend on the stock price (Eckbo, Masulis, and Norli, 2007); managerial compensation contracts often depend in varying ways on the firm's stock price (e.g., Frydman and Jenter, 2010; Bennett et al., 2019); managerial turnover decisions are affected by the stock price (Warner, Watts, and Wruck, 1988); and so on. A vast literature in finance reaches conclusions about firm policies and managerial performance based on comparison of a firm's stock price to the stock price of other firms. Reactions of the stock market to firm decisions are the object of event studies, but they are also the object of attention from managers, board members, and investors. At times, firms change decisions based on the reaction of the stock market or take decisions because

they expect the stock market to react favorably to them. Shareholders react to firm decisions and as a result may choose to sell shares.

Those who argue that the stock market signals hurt the economy because they lead managers to take actions that boost the stock price quickly at the expense of long-term wealth creation would not be surprised by evidence that management responds to stock market signals (e.g., Foroohar, 2016). The key issue is whether these signals improve welfare. To resolve this question, one would want to see evidence that stock market signals have a real impact rather than an impact on stock market metrics. If the stock market leads to poor allocation of resources, then it must be rewarding poor allocation of resources. The use of productivity as a metric has the advantage of being a summary measure of firm efficiency that does not depend on stock market valuations.

Even if the stock market's signals lead to a more efficient allocation of resources, it does not follow from the fact that if a firm pays attention to the stock price, then its actions will increase productivity. With constant returns to scale, for instance, a firm that increases its scale would not become more productive. Hence, whether information in the stock price leads firms to become more productive is an empirical question. However, while investment decisions often affect the scale of operations, many other decisions do not affect the scale of operations but rather the efficiency of operations. It follows that decisions other than investment decisions may be more likely to have an impact on productivity. For instance, the decision to fire a CEO is likely to depend in part on the stock price. We would expect such a decision, in general, to improve the operations of the firm if taken.

3. Measures of stock price informativeness

We highlight the results using two measures of stock price informativeness, which are annual measures based on stock trades or daily stock returns, but also show results using other measures. The first measure is the probability of information-based trading (PIN), which follows from a market microstructure model (Easley, Hvidkjaer, and O'Hara, 2002). The logic is that, when there is more informed trading in a stock, new information is more likely to be incorporated into that stock's price, which improves the stock's price informativeness. High PIN means high SPI. The second measure is the stock's price nonsynchronicity (PSI), which captures the firm-specific stock return variation

(Durnev, Morck, and Yeung, 2004). The logic is that, when there is more firm-specific information in the stock price, the stock return is less correlated with market and industry returns. High PSI means high stock price informativeness. Both measures are widely used as stock price informativeness measures in the literature.[1]

3.1. Probability of information-based trading (PIN)

PIN measures the probability of information-based trading. Suppose that on a day new information appears with probability α, with probability δ the news is bad, and with probability $1 - \delta$, the news is good. The probability of no news on a day is $1 - \alpha$. The trading orders follow Poisson distributions. Uninformed traders trade irrespective of whether new information arrives or not. The arrival rate of uninformed buy (sell) orders is $\varepsilon_b(\varepsilon_s)$. The traders with private information only trade when there is new information, and the arrival rate is μ. The informed trader will only buy if the news is good and only sell if the news is bad. Given these parameters $(\alpha, \delta, \mu, \varepsilon_b, \varepsilon_s)$, the probability of information-based trading is

$$\text{PIN} = \frac{\alpha \cdot \mu}{\alpha \cdot \mu + (\varepsilon_b + \varepsilon_s)}, \tag{1}$$

where the denominator is the arrival rate for all orders and the numerator is the arrival rate of informed orders.

The parameters are estimated by maximum likelihood. On day i, we observe the number of buy orders B_i and the number of sell orders S_i. Denote the Poisson distribution function as $P(k; \lambda) = e^{-\lambda} \frac{\lambda^k}{k!}$, where k is the number of arrivals and λ is the arrival rate. The likelihood of information-based trading on a given trading day is

$$L(\alpha, \delta, \mu, \varepsilon_b, \varepsilon_s | B_i, S_i) = (1 - \alpha) \cdot P(B_i; \varepsilon_b) \cdot P(S_i; \varepsilon_s) + \alpha \cdot \delta \cdot P(B_i; \varepsilon_b) \cdot P(S_i; \mu + \varepsilon_s)$$

$$+ \alpha \cdot (1 - \delta) \cdot P(B_i; \mu + \varepsilon_b) \cdot P(S_i; \varepsilon_s). \tag{2}$$

Assuming that trading activity across days is independently distributed, the likelihood function within a year is

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[1] For example, see Chen, Goldstein, and Jiang (2007) and Ferreira, Ferreira, and Raposo (2011).

$$V = \prod_{i=1}^{I} L(\alpha, \delta, \mu, \varepsilon_b, \varepsilon_s | B_i, S_i), \tag{3}$$

where I is the number of trading days in a year.

Based on trade and quote (TAQ) data and the Lee and Ready (1991) algorithm, we calculate the number of daily buy and sell orders for a stock. We then use maximum likelihood to calculate the parameters $(\alpha, \delta, \mu, \varepsilon_b, \varepsilon_s)$ based on the data in a year. In turn, PIN is calculated for a stock in a given year.

3.2. Stock price nonsynchronicity (PSI)

The stock price nonsynchronicity, PSI, is a measure of stock price informativeness based on the R^2 from asset pricing regressions, following Roll (1988) and Morck, Yeung, and Yu (2000). We decompose the stock return into the systematic part explained by the market return and industry return and firm-specific residual variation. When there is relatively more firm-specific variation, the return co-moves less with the market return and the industry return, so R^2 is smaller. To perform our decomposition, we use the following linear regression:

$$r_{j,i,t} = \beta_{j,0} + \beta_{j,m} r_{m,t} + \beta_{j,i} r_{i,t} + \varepsilon_{i,j,t}, \tag{4}$$

where j is for firm j, i is for industry i, and t is for day t, $r_{j,i,t}$ is the stock return of firm j in industry i defined at the three-digit standard industrial classification (SIC) on day t, $r_{m,t}$ is the value weighted market return on day t, and $r_{i,t}$ is the value weighted industry return on day t. The weights are based on market capitalization. When calculating the market and industry value weighted returns for firm j, the return of firm j is excluded to prevent spurious correlations between firm and industry returns in industries that contain few firms.

The regression is estimated for each firm j within a year, and the R^2 of the regression is used to construct PSI_j for stock j in a given year as follows:

$$PSI_j = \ln\left(\frac{1 - R_j^2}{R_j^2}\right). \tag{5}$$

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In the above equation, PSI_j is transformed to address the skewness and boundedness of $1 - R_j^2$ (Morck, Yeung, and Yu, 2000). The stock price is more informative when a stock becomes less correlated with the market and industry returns (i.e., when R_j^2 falls and hence PSI_j increases).

3.3. Additional measures of stock price informativeness

Besides PIN and PSI, we also investigate the relation between SPI and TFP using two additional SPI measures: Gamma and Adjusted PIN. Gamma measures the amount of trading-based information in stock prices. It is originally constructed by Llorente, Michaely, and Wang (2002) and used by Frésard (2012) and Foucault and Frésard (2014). We apply two versions of Gamma. The first version follows Llorente, Michaely, and Wang (2002) and Frésard (2012), in which both the firm stock return and the market return are controlled for in the calculation of Gamma. We denote this version as Gamma(Market). The second version follows an original design by Llorente, Michaely, and Wang (2002), in which only the firm stock return is controlled for in the calculation of Gamma. We denote this version as Gamma(No market). Duarte and Young (2009) develop Adjusted PIN, which we denote by APIN. APIN refines PIN by removing the liquidity component of PIN so that only the portion related to asymmetric information remains.

4. Data and sample

Our firm-level accounting data are from Compustat. We use TAQ data to calculate PIN and the daily stock file from the Center for Research in Security Prices (CRSP) to calculate PSI. Mutual fund data are from the Thomson-Reuters mutual fund holdings database and CRSP mutual fund database. Institutional ownership and blockholder data are from Thomson-Reuters 13F. CEO turnover data are from ExecuComp. Corporate governance related data are from RiskMetrics. The product market competition variables we use are from the Hoberg-Phillips data library.[2]

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[2] We thank Hoberg and Phillips for making the competition measures publicly available: http://hobergphillips.usc.edu/.

Our sample only includes firms with nonmissing accounting data and nonmissing stock price informativeness (we require at least one of PIN or PSI for a firm-year to be included in our sample). PIN is first available in 1993, as that is the first year TAQ data are available. In our analysis, we use the average PIN and PSI over the previous three years (we require at least one nonmissing value in the previous three years). We use a backward-looking approach to help alleviate reverse causality concerns. Our sample is from 1994 to 2015 and includes 66,341 firm-year observations.

Our main dependent variable is TFP. TFP measures the overall effectiveness and efficiency with which capital and labor are used in the production process. We estimate the production function following Ackerberg, Caves, and Frazer (2015). Compared with earlier methods (Olley and Pakes, 1996; Levinsohn and Petrin, 2003), Ackerberg, Caves, and Frazer (2015) address the functional dependence problem and estimate all input coefficients in the second stage of the estimation. The detailed description of our method to estimate TFP can be found in Appendix B.

The control variables used in our main tests are the natural logarithm of total assets, Tobin's q, cash scaled by assets, debt scaled by assets, and research & development (R&D) scaled by assets. The definitions for all variables can be found in Appendix A. The summary statistics of our main variables are reported in Table 1. The mean values of our SPI variables, PIN and PSI, are 0.22 and 2.22, respectively, which are in line with previous studies.[3]

5. Empirical evidence

In this section, we first present our baseline ordinary least squares (OLS) regressions. We then turn to various approaches to account for endogeneity.

5.1. Baseline regressions

If more informative stock prices help make firms more productive, we should find a positive relation between TFP and SPI. Our baseline regression specification regresses TFP on lagged average SPI and controls for firm characteristics, year fixed effects, and firm fixed effects:

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[3] See Chen, Goldstein, and Jiang (2007) and Ferreira, Ferreira, and Raposo (2011).

$$TFP_{it} = \beta_0 + \beta_1 \cdot SPI_{i,t-3,t-1} + X_{it} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}, \qquad (6)$$

where i is the firm index, t is the year index, $SPI_{i,t-3,t-1}$ stands for the measure of stock price informativeness, which is the average of the previous three years,[4] X is the vector of control variables, Γ is the coefficient vector for the control variables, μ_i is the firm fixed effect, ϑ_t is the year fixed effect, and ε_{it} is the error term. The results are reported in Table 2.

Panel A of Table 2 shows the results for our main SPI measures, PIN and PSI. Models 1 and 3 use PIN as the SPI measure. Model 1 controls for firm size and Tobin's q. Model 3 also includes cash holdings, leverage, and R&D as control variables. We use the full list of control variables in Model 3 in the remainder of the paper. We include firm fixed effects to minimize potential issues related to time-invariant firm-specific omitted variables. Estimated coefficients on PIN are positive and highly significant in both models (*t*-statistics above 8). Models 2 and 4 use PSI as the SPI measure. The results are consistent with those using PIN. The economic effects are also significant. One standard deviation increase in PIN (PSI) leads to a 5% (5%) TFP increase in standard deviation units, based on the results in Models 3 (4).

When we use PSI as the measure of SPI, we can have a longer sample period because its calculation relies on the CRSP daily stock files. Model 5 estimates Model 4 from 1962 to 2015. The coefficient on PSI is significantly positive, but its economic magnitude is lower.

The literature has documented that the sensitivity of capital expenditures to Tobin's q increases with SPI (Chen, Goldstein, and Jiang, 2007). The literature has not explored whether the greater sensitivity of investment to q due to higher SPI leads to a greater impact of investment on TFP. To assess the importance of this investment channel for our results, we reestimate Models 3 and 4, adding investment variables. These variables are capital expenditures divided by assets, the capital expenditures sensitivity to Tobin's q (investment-q sensitivity), and the interaction between the capital expenditures sensitivity to Tobin's q and capital expenditures.[5] We find that the SPI coefficients are

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[4] In unreported tests, we also use the average SPI of the previous two or four years. Our results remain strong and are not sensitive to the time window for the average.

[5] A firm's capital expenditures sensitivity to Tobin's q is calculated by regressing capital expenditures (scaled by total assets) on lagged Tobin's q, logarithm of total assets, and cash flows in a five-year rolling window. The coefficient of Tobin's q is the capital expenditures sensitivity to Tobin's q (investment-q sensitivity or IQS). The potential measurement error in q is addressed by using the approach of Erickson and Whited (2000).

largely unchanged, which suggest that the contribution of the investment channel to our results is limited. Nevertheless, the interaction of investment efficiency with the level of capital expenditures is positive in both models and significant in Model 7, so there is evidence that investment by firms with higher SPI is associated with higher productivity. In other words, investment contributes more to productivity when it is made by a firm with better price discovery.

Panel B of Table 2 shows the results for our additional SPI measures. Models 1, 2, 4, and 5 show that the coefficients of Gamma (both versions) are significantly positive. In Models 3 and 6, the estimated coefficients on the Adjusted PIN (APIN) are significantly positive as well.

Though we do not tabulate the results, we perform additional robustness checks. First, we split our sample period. We find that our results hold similarly for both halves of our sample period. Second, we calculate TFP at the two-digit SIC industry level so that we allow production functions to differ across industries. Our conclusions are the same.

5.2. Endogeneity tests

In Section 5.1, we reported the results from OLS regressions using different measures of SPI, different sample periods, and different control variables. All the estimates of the coefficients on the measures of SPI are significantly positive. In all the regressions, we use lagged values of the right-hand side variables to mitigate reverse causation concerns and use firm fixed effects to account for time-invariant unobserved firm-specific variables. In this section, we further address endogeneity concerns through analyses using brokerage house research department closures, S&P 500 index additions, and mutual fund redemptions as plausibly exogenous events.

5.2.1. Brokerage research department closures

We first use brokerage house research department closures as exogenous shocks to the information production of the covered stocks (Kelly and Ljungqvist, 2012; Derrien and Kecskes, 2013). These research departments produce information that they make available to their clients, including both institutional and retail clients. When research departments are closed, less information on the firms they cover is available to institutional and retail investors. We therefore expect the SPI for the stocks of these

firms to fall. The closure of a brokerage house research department has little or nothing to do with the fundamentals of the covered firms. Therefore, these shocks to the firms' stocks are largely exogenous.

5.2.1.a. Stock price informativeness and brokerage research department closures

We first show evidence that brokerage research department closures affect stock price informativeness. To identify closures of brokerage houses, we start from the closures listed in Kelly and Ljungqvist (2012). We match the closure dates with the "delisting" (last) date of brokerage houses and the number of firms they cover in the Institutional Brokers' Estimate System (IBES). Of the 22 closures listed, we use Bloomberg and Factiva to manually identify 17 closures using the last date a brokerage appears in IBES and the number of firms it covers. We define a dummy variable Closure that equals one if a stock is covered by a closed research department in the previous one or two years before closure and zero otherwise. We then regress PIN and PSI on Closure and relevant control variables. Firm and year fixed effects are included in the tests. The results are reported in Table 3.

Model 1 (2) of Table 3 shows the effect of brokerage closures on PIN (PSI). The coefficients of Closure in both models are negative and statistically significant at the 5% level. These results confirm that stock price informativeness is reduced significantly by brokerage closures. The evidence supports the hypothesis that brokerage research department closures can be used as exogenous reductions in stock price informativeness.

5.2.1.b. Event study: DiD analysis based on brokerage research department closures

To study the effect of price informativeness on TFP, we carry out a DiD analysis based on the brokerage research department closures. Specifically, we construct a propensity score matched (PSM) sample, in which the treated firms are those that experience brokerage closures and control firms are those that do not. We first restrict the potential control firms to those i) that have at least one analyst covering the firm, ii) are not covered by any of the 17 brokerage houses that ultimately close, and iii) have Compustat data available during the sample period. We then match treated firms to control firms using the Mahalanobis distance. We only consider matches in the same two-digit SIC code and then find the closest firm in terms of the total assets and Tobin's q.

We first show a graphical analysis of the relation between TFP and brokerage closures following an approach used in the literature (Autor, Donohue, and Schwab, 2006; Acharya, Baghai, and Subramanian, 2014; Serfling, 2016). Specifically, we regress TFP on dummy variables indicating the year relative to the closure year and control for year fixed effects and firm size. The coefficients for the dummy variables are shown in Fig. 1. The dashed lines are for the 90% confidence intervals of the coefficient estimates, and the confidence intervals are based on standard errors clustered at the firm level. The figure shows that productivity (TFP) is not statistically different between treated and control firms three years before the event year. This shows that the parallel trend condition for the DiD analysis is satisfied. Furthermore, in the years after the closures, the TFP of the treated firms is significantly lower than that of control firms.

We then estimate regressions for the DiD analysis. The first closure event is in 2000 and the last is in 2007. For each closure event, we define an event window from four years before to four years after the closure event.[6] It leads to a test sample from 1996 to 2011. Specifically, we define a dummy variable, Treatment_post, which equals one if a firm experienced a brokerage closure over the previous four years and zero otherwise. The DiD specification is as follows:

$$TFP_{it} = \beta_0 + \beta_1 \cdot Treatment\_post_{it} + X_{it} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}, \qquad (7)$$

where i is the firm index, t is the year index, X is the vector of control variables, Γ is the coefficient vector of the controls, μ_i is the firm fixed effect, ϑ_t is the year fixed effect, and ε_{it} is the error term. We drop the year of the closure in the regression analysis. The estimates are reported in Table 4.

Model 1 shows that the coefficient of Treatment_post is negative and statistically significant at the 5% level. It indicates that negative shocks to SPI have a negative impact on the treated firms' productivity. Specifically, compared to the control firms, the treated firms experience a 4.3% TFP decrease in standard deviation units. This result supports the causal interpretation of the estimates of the coefficients of SPI in regressions of TFP on SPI.

To study how the effects of price informativeness on TFP evolve across years after the closure, we further define one dummy variable for each year after the closure event, and accordingly, we have four

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[6] Our results are robust to a different event window three years before to three years after a brokerage closure.

dummy variables. We replace the treatment variable Treatment_post in the previous test by these individual dummy variables and use the following specification:

$$TFP_{it} = \beta_0 + \sum_{k=1}^{4} \beta_k \cdot I_k + X_{it} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}, \qquad (8)$$

where i is the firm index, t is the year index, I_k is a dummy variable that equals one when it is k year(s) after a brokerage closure and zero otherwise, X is the vector of control variables, Γ is the coefficient vector of the controls, μ_i is the firm fixed effect, ϑ_t is the year fixed effect, and ε_{it} is the error term. The estimates are reported in Model 2 of Table 4.

Model 2 shows that the coefficients β_1 to β_4 are all significantly negative, consistent with the results of Model 1. When time moves on, these coefficients become smaller (about 5% for the first two years and 4% for the last two years), and the significance level goes from the 1% level to the 10% level. We would expect that, over time, other analysts might start covering the firm and investors might start collecting more information about the stock. These developments should attenuate the effect of brokerage closures. The estimates in Model 2 also support the interpretation that the post-event decrease in TFP of treated firms is caused by the brokerage house closures that serve as negative exogenous shocks to SPI.

5.2.2. S&P 500 index additions

The firms in the S&P 500 index are selected by a committee based on eight primary criteria.[7] The selected firms have little control on the selection process, so research examining the impact of additions to the S&P 500 index typically treats the event as exogenous (see, for instance, Harris and Gurel, 1986; Shleifer, 1986).[8] Existing research shows that prices of S&P 500 stocks are more likely to comove with the index (Vijh, 1994; Barberis, Shleifer, and Wurgler, 2005). Greater comovement implies that less firm-specific information is incorporated in the stock prices of firms in the index. As a result, if a firm

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[7] The primary criteria include specific requirements on the following eight dimensions: market capitalization, liquidity, domicile, public float, sector classification, financial viability, length of time publicly traded, and stock exchange. More details can be found at http://us.spindices.com/documents/methodologies/methodology-sp-us-indices.pdf.

[8] An exception is Denis et al. (2003).

is added to the index, its stock price informativeness falls. Accordingly, we expect that being added to the index reduces a firm's productivity.

5.2.2.a. Stock price informativeness and S&P 500 additions

We first show evidence that S&P 500 additions have a negative effect on stock price informativeness. We define a dummy variable Addition that equals one if a firm is added to the S&P 500 index in the previous one or two years and zero otherwise. We then regress PIN and PSI on Addition and relevant control variables. Firm and year fixed effects are included in these tests. The test sample includes firms with above-median book assets because firms added to S&P 500 Index are unlikely to have assets below median assets. The results are reported in Table 5.

Model 1 shows the effect of S&P additions on PIN and Model 2 shows the effect on PSI. The coefficients of Addition in both models are negative and statistically significant at the 10% and 5% level, respectively. These results confirm that the stock price informativeness decreases significantly after a firm is added into the S&P 500 index. The evidence supports the idea that S&P 500 additions serve as exogenous decreases in stock price informativeness.

5.2.2.b. Event study: DiD analysis based on S&P 500 additions

In this section, we carry out a DiD analysis based on the events of S&P 500 additions. Specifically, we construct a PSM sample, where the treated firms are those that are added to the S&P 500 index and the control firms are those that are not. We restrict the potential control firms to firms i) that are never added to the S&P 500 index at any time during the sample period and ii) have Compustat data available during the sample period. We then match treated firms to control firms using the Mahalanobis distance. We only consider matches in the same two-digit SIC code and then find the closest firm in terms of total assets and Tobin's q.

Similar to the DiD analysis based on brokerage house closures, we first show a graphical analysis of the relation between TFP and S&P 500 index additions. Specifically, we regress TFP on dummy variables indicating the year relative to the index addition year and control for year fixed effects and firm size. The coefficients for dummy variables are shown in Fig. 2, in which the vertical axis is for

these estimated coefficients and the horizontal axis is for the time relative to the index addition events. The dashed lines are for the 90% confidence intervals of the coefficient estimates, and the confidence intervals are based on standard errors clustered at the firm level. The figure shows that productivity (TFP) is not statistically different between treated and control firms three years before the event year. This shows that the parallel trend condition for the DiD analysis is satisfied. Furthermore, in the years after index additions, the TFP of the treated firms is significantly lower than that of control firms.

We then estimate regressions for the DiD analysis. For each S&P 500 index addition, we define an event window from four years before to four years after the index addition.[9] We define a treatment dummy, SP500_addition, which equals one if a firm was added to the S&P 500 index over the previous four years and zero otherwise. The DiD specification is as follows:

$$TFP_{it} = \beta_0 + \beta_1 \cdot SP500\_addition_{it} + X_{it} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}, \tag{9}$$

where i is the firm index, t is the year index, X is the vector of control variables, Γ is the coefficient vector of the controls, μ_i is the firm fixed effect, ϑ_t is the year fixed effect, and ε_{it} is the error term. The estimates are reported in Table 6. Model 1 shows that a firm's TFP is significantly reduced after it is added to the S&P 500 index.

There might be concerns that firms with better performance are more likely to be selected in the index and the decrease in TFP after additions could be normal mean reversion in firm performance. We address this potential concern by using additional matching criteria on firms' performance before index additions, in which the additional criteria are the firm's stock return or its lagged TFP. Specifically, for each firm added to the S&P 500 index, we select a neighbor firm in terms of total assets, Tobin's q, and either the stock return over the previous 12 months or lagged TFP. The results are reported in Models 2 and 3, respectively. The results show that firms' productivity is reduced after index additions, which is consistent with the evidence in Model 1.

One might be concerned that, after a stock is added to the index, its liquidity increases. Further, the cost of equity of the firm could fall. However, there is no good reason to expect that an increase in stock liquidity and a decrease in the cost of equity cause a decrease in productivity. Therefore, these effects

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[9] Our results are robust to a different event window three years before to three years after an S&P 500 index addition.

are more likely to weaken the negative effects of the decrease in SPI on productivity than to strengthen it. We address these concerns in Models 4 and 5 by further controlling for stock liquidity, return, and institutional ownership. Our results are robust to these additional controls.[10]

To study how the effects of index additions on TFP evolve across years, we define an individual dummy variable for each year after a closure event, and accordingly, we have four dummy variables. The specification is as follows:

$$TFP_{it} = \gamma_0 + \sum_{k=1}^{4} \gamma_k \cdot I_k + X_{it} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}, \tag{10}$$

where i is the firm index, t is the year index, I_k is a dummy variable that equals one when it is k year(s) after an index addition and zero otherwise, X is the vector of control variables, Γ is the coefficient vector of the controls, μ_i is the firm fixed effect, ϑ_t is the year fixed effect, and ε_{it} is the error term. The estimates are reported in Model 6. The estimates show that all coefficients γ_1 to γ_4 are significantly negative. The effect in the first year after an index addition is relatively weaker and only statistically significant at the 10% level. The coefficients γ_2 to γ_4 are larger and all statistically significant at the 1% level. It follows that a firm's productivity is significantly reduced after the index addition, and the negative effects are persistent.

5.2.3. Mutual fund redemption shock

We further use mutual fund flow redemption pressure as an exogenous shock to price informativeness and show how a decrease in price informativeness reduces productivity. The literature shows that mutual fund redemptions bring downward pressure on the price of the stocks they hold and this effect is unrelated to firm fundamentals (Coval and Stafford, 2007; Edmans, Goldstein, and Jiang, 2012; Dessaint et al., 2019). These fund flow events fit well with the intuition that the affected stock

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[10] When combining the findings in Tables 2 and 5, one might be tempted to conclude that the effect of S&P additions on TFP (through PSI) is $-0.154 \times 0.02 \approx -0.003$. In contrast, when using a DiD analysis, the reduced-form estimate of this relation in Table 6 (Column 5) is -0.058, which is larger. The DiD analysis estimates the treatment effect of being added to the S&P by comparing firms added to the S&P 500 to similar firms. In contrast, the regressions in Table 2 estimate average effects for the two samples. Consequently, the coefficients are not comparable. However, it is also worth noting that a 95% confidence interval for the coefficient -0.058 in Table 6 is $[-0.111, -0.005]$ so that the upper bound of the interval is close to the inferred coefficient of -0.003.

prices become less informative because lower stock prices after such a shock are less likely to signal that firm fundamentals have worsened.

To be more specific, mutual fund flow pressure can have negative effects on stock price informativeness for the following two reasons. First, mutual funds with outflow pressure reduce their stock holdings for liquidity reasons. These liquidity-driven trades increase the fraction of uninformed trades in the market. Accordingly, the fraction of informed trades becomes relatively smaller, and as a result, stock prices become less informative (Easley et al., 1996; Easley, Hvidkjaer, and O'Hara, 2002). Second, mutual fund pressure drives stock prices away from their fundamental value, which decreases investors' incentives to collect private information on firm fundamentals for trading purposes: collecting private information is costly, but less valuable, because stock price variation is more influenced by factors unrelated to fundamentals.

To measure a stock's mutual fund flow pressure, we follow Edmans, Goldstein, and Jiang (2012) and use the stock's hypothetical sales by mutual funds that hold this stock and experience large fund outflows (at least 5% of a fund's total assets). In contrast to actual sales, hypothetical sales alleviate endogeneity concerns because actual sales of mutual funds are likely influenced by managers' views about firm fundamentals. We define a mutual fund flow pressure indicator variable MFFlow, which equals one if a stock's hypothetical mutual fund sales are positive in a year and zero otherwise. A stock with mutual fund flow pressure is expected to experience a decrease in informativeness due to a drop in stock price unrelated with firm fundamentals.

The negative relation between mutual fund flow pressure and stock price informativeness is confirmed by the data. We regress SPI measures on MFFlow and control variables using the following specification:

$$SPI_{it} = \beta_0 + \beta_1 \cdot MFFlow_{i,t-1} + X_{i,t-1} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}, \tag{11}$$

where i is the firm index, t is the year index, SPI is PIN or PSI, MFFlow is the mutual fund flow pressure indicator, X is the vector of control variables, Γ is the coefficient vector of the controls, μ_i is the firm fixed effect, ϑ_t is the year fixed effect, and ε_{it} is the error term. Results are reported in Table 7. The

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coefficients on PIN and PSI are both negative and statistically significant at the 1% level. The results confirm that the mutual fund flow pressure significantly reduces stock price informativeness.

We then show the direct evidence that the mutual fund flow pressure has a negative effect on firms' productivity. Our specification is as follows:

$$TFP_{it} = \beta_0 + \beta_1 \cdot MFFlow_{i,t-1} + X_{it} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}, \tag{12}$$

where i is the firm index, t is the year index, MFFlow is the mutual fund flow pressure indicator as defined above, X is the vector of control variables, Γ is the coefficient vector of the controls, μ_i is the firm fixed effect, ϑ_t is the year fixed effect, and ε_{it} is the error term. Results are reported in Table 8. Models 1 and 2 show that the coefficients of MFFlow, β_1, is negative and statistically significant at the 1% level.[11] These results show that an exogenous decrease in price informativeness due to mutual fund flow pressure significantly reduces firms' productivity.

In this section, the analyses based on brokerage house closures, S&P 500 index additions, and mutual fund flow pressure all provide strong and consistent support for the causal effect of SPI on TFP. These results are consistent with the view that financial markets have real effects on the economy through their informational role.

6. How does price informativeness affect TFP?

In this section, we provide evidence on channels through which stock price informativeness affects TFP. Specifically, we use mutual fund flow redemption pressure and brokerage house closures as exogenous shocks to price informativeness and show that CEO turnover is less sensitive to Tobin's q when price becomes less informative. We then investigate how price informativeness affects firms' inputs and outputs, which are determinants of productivity.

6.1. Price informativeness, CEO turnover, and productivity

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[11] In an unreported test, we further control for the stock return to address the concern that the decrease in TFP is only driven by the decrease in the stock price, and our result is robust.

In this paper, we investigate whether firms learn from stock price changes in such a way that what they learn helps them become more productive. If a firm's stock price is more informative, firms learn more from stock price changes. When a firm's stock price is less informative, management and investors put less weight on changes in stock prices when they assess firm performance and when they infer how the market values actions taken by management. Another way to put this is that the noisier the stock price, the less weight management puts on the stock price in its decision-making. As we explained in the previous section, a key issue in assessing whether SPI impacts TFP is that both SPI and TFP may be jointly affected by common factors, so a relation between SPI and TFP reflects the impact of changes of common factors rather than the impact of a change in SPI on TFP. We showed that the relation between SPI and TFP can be interpreted causally using three types of exogenous variation in SPI. These analyses did not, however, show how shocks to informativeness affect TFP.

In this section, we provide evidence on this question. Specifically, we use mutual fund redemption pressure and brokerage firm closures as exogenous shocks to stock price informativeness.[12] We show that the induced decrease in stock price informativeness causes a decrease in the responsiveness of CEO turnover to Tobin's q. As CEO turnover falls because of the shock, productivity falls as well.

6.1.1. Mutual fund flow pressure and CEO turnover

It is well shown in the literature that boards use a firm's stock price as a measure of CEO performance when making decisions on CEO turnover (Warner, Watts, and Wruck, 1988; Coughlan and Schmidt, 1985; Huson, Parrino, and Starks, 2001). However, when the stock price becomes less informative, we expect that boards optimally decrease the weight they put on the firm's stock price when assessing CEO performance. For example, when a firm's stock experiences large mutual fund flow pressure, the board would not want to attribute much of the drop in firm value to actions taken by

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[12] From the previous section, we know that S&P 500 index additions decrease stock price informativeness and productivity. This evidence suggests we should find the same impact on turnover-q sensitivity of such shocks that we find for brokerage closures and mutual fund redemption shocks. However, additions to the index are accompanied by an increase in institutional ownership, which may increase attention paid to the firm and to the performance of the CEO. This effect is a countervailing force, so the net impact of addition on the q sensitivity of turnover may be attenuated. It is therefore not surprising that we find the impact of S&P 500 index additions on the q sensitivity of turnover to be insignificant.

the CEO because it may be due, in part, or completely, to flow pressure unrelated to CEO performance. As the stock price becomes a poorer measure of CEO performance, we expect that CEO turnover becomes less likely and less sensitive to Tobin's q. Importantly, if the CEO's bad performance is disguised by the effect of mutual fund flow pressure on the stock price, failing to replace the CEO because of low stock price informativeness has a negative impact on the firm's productivity. This illustrates one concrete channel through which stock price informativeness affects productivity.

To test the effect of stock price informativeness on CEO turnover, we collect turnover data from the ExecuComp database during our sample period (1994 to 2015). The regression specification used in our tests is as follows:

$$Turnover_{it} = \beta_0 + \beta_1 \cdot Q_{t-1} \cdot MFFlow_{i,t-2} + \beta_2 \cdot Q_{t-1} + \beta_3 \cdot MFFlow_{i,t-2} + X_{i,t-1} \cdot \Gamma + \mu_j + \vartheta_t$$
$$+ \varepsilon_{it}, \tag{13}$$

where i is the firm index, j is the industry index, and t is the year index, Turnover is a dummy variable that equals one if a firm has a CEO turnover in a year and zero otherwise, X is the vector of control variables, Γ is the coefficient vector of the controls, μ_j is the industry fixed effect, ϑ_t is the year fixed effect, and ε_{it} is the error term.[13] Our focus is on the coefficients β_1 and β_2. We expect the sign of β_1 to be opposite of the sign of β_2, which indicates that mutual fund pressure weakens the turnover sensitivity to Tobin's q. We estimate logit regressions and estimates are reported in Panel A of Table 9.

Model 1 shows that the coefficient of Tobin's q is negative and statistically significant at the 1% level. It is consistent with the intuition that a lower market valuation makes CEO turnover more likely. More importantly, the coefficient of the interaction between q and MFFlow is positive and statistically significant at the 1% level. The opposite sign of the coefficient of q and the coefficient of the interaction term confirms that mutual fund flow pressure makes the turnover decisions less sensitive to the market valuation of the firm. Furthermore, the coefficient of MFFlow is negative and statistically significant at the 1% level.[14] This is consistent with the idea that flow pressure makes price less informative and hence reduces the sensitivity of CEO turnover to price. Model 2 further controls for firms' return on assets

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[13] We use mutual fund flow pressure one year before the timing of Tobin's q to alleviate the effect of flow pressure on q. Our results are robust when using flow pressure in the same year as q.

[14] This result is robust if we do not include the interaction between q and MFFlow.

(ROA) and includes a dummy variable Old CEO, which equals one if a CEO is older than 60 and zero otherwise. Our results are robust to these additional controls.

6.1.2. Brokerage house closures and CEO turnover

We also use brokerage house closure as an exogenous shock to price informativeness and investigate its effect on CEO turnover sensitivity to q. Specifically, we use the same PSM sample and [-4, 4] event window as in Section 5.2.1. The specification of the logit model is the following:

$$Turnover_{it} = \beta_0 + \beta_1 \cdot Q_{t-1} \times Closure\_post_{i,t} + \beta_2 \cdot Q_{t-1} + \beta_3 \cdot Closure\_post_{i,t} + X_{i,t-1} \cdot \Gamma$$

$$+ \mu_j + \vartheta_t + \varepsilon_{it}, \tag{14}$$

where i is the firm index, j is the industry index, t is the year index, Turnover is a dummy variable that equals one if a firm has a CEO turnover in a year and zero otherwise, Closure_post is a dummy variable that equals one if a firm experienced a brokerage closure in the previous four years, X is the vector of control variables, Γ is the coefficient vector of the controls, μ_j is the industry fixed effect, ϑ_t is the year fixed effect, and ε_{it} is the error term. Our focus is on the coefficients β_1 and β_2. We expect that the sign of β_1 is opposite to that of β_2, which indicates that brokerage house closures weaken the turnover sensitivity to Tobin's q. We estimate logit regressions, and estimates are reported in Panel B of Table 9.

Consistent with the results in Panel A, the coefficient of Tobin's q, β_2, is negative, and the coefficient of the interaction term, β_1, is positive and statistically significant at the 10% or 5% level in Models 1 and 2, respectively. The sign of β_1 is opposite to that of β_2, which means that brokerage house closures reduce the turnover sensitivity to Tobin's q. These results show that the decrease in price informativeness has a negative effect on the q sensitivity of turnover.

6.1.3. CEO turnover and improvements of productivity

Sections 6.1.1 and 6.1.2 show that an exogenous shock to stock price informativeness makes CEO turnover less likely. We now provide further evidence on the link between SPI and productivity by

showing CEO turnover is followed by higher firm productivity. This means that when lower stock price informativeness prevents CEO changes that would otherwise happen, firm productivity can be negatively affected. We estimate the following regression:

$$\Delta TFP_{it} = \beta_0 + \beta_1 \cdot Turnover_{t-1} + Turnover_{i,t-2} + X_{i,t} \cdot \Gamma + \mu_j + \vartheta_t + \varepsilon_{it}, \qquad (15)$$

where i is the firm index, t is the year index, Δ is the first-difference operator, X is the vector of control variables, Γ is the coefficient vector of the controls, μ_i is the firm fixed effect, ϑ_t is the year fixed effect, and ε_{it} is the error term. The estimates are reported in Table 10.

Model 1 shows that CEO turnover two years ago is followed by a significant improvement in firm productivity (at the 5% level). The coefficient on last year's turnover is also positive but not statistically significant. This shows that it takes a new CEO two years to improve firm productivity. Model 2 includes the indicator variable for turnover three years ago to investigate whether the improvements of TFP reverse in later years. The result shows that firm productivity remains stable after the improvements. It means the improvement of productivity due to CEO turnover is not a temporary effect.

Our findings show that stock price informativeness affects firms' ability to learn from the stock price and to use it as a signal for efficiency improvement, such as whether to replace a CEO. When changes in price are less informative, firms have less information to make decisions and hence are less likely to take actions because they are less sure that these actions are optimal. These findings illustrate one concrete channel through which stock price informativeness affects firm productivity.

6.2. Price informativeness, inputs, and outputs

SPI can affect TFP by increasing output for given inputs and by decreasing inputs for given output. Consequently, to understand how SPI affects TFP, it is useful to assess separately how it affects inputs and output. The inputs that we consider include firms' general operating expenses (SG&A, scaled by total assets) and labor costs. We use revenue as the measure of output. We expect that SPI increases output and decreases inputs, which in turn leads to a TFP improvement. Our specification is as follows.

$$IO_{it} = \beta_0 + \beta_1 \cdot SPI_{i,t-3,t-1} + X_{it} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}, \qquad (16)$$

where i is for firm i, t is for year t, IO stands for the measures of input and output, $SPI_{i,t-3,t-1}$ stands for PIN or PSI averaged over the previous three years, X is the vector of control variables, Γ is the coefficient vector of the controls, μ_i is the firm fixed effect, ϑ_t is the year fixed effect, and ε_{it} is for the error term. The results are reported in Table 11.

Models 1 and 2 show that SPI increases output as measured by the logarithm of revenues. The coefficients of PIN and PSI are both positive and significant at the 1% level, which indicates that SPI has a positive effect on firm output. Models 3 and 4 show that SPI decreases general operating costs (SG&A, scaled by total assets). The coefficients of PIN and PSI are both negative and statistically significant at the 1% or the 5% level. These estimates are consistent with the idea that informative stock prices facilitate market monitoring and drive managers to allocate SG&A expenditures better to improve efficiency. Models 5 to 6 show that SPI decreases labor costs. The coefficients on both SPI measures are all significantly negative and indicate that firms with more informative stock prices spend less on wages. Specifically, a one standard deviation increase in PIN (PSI) decreases wage payments by 3% (3%). These real effects on the revenues, SG&A, and labor costs identify concrete channels through which SPI affects TFP.

7. Cross-sectional heterogeneity

As explained in the introduction, we expect the ability and incentives of firms to take advantage of stock price informativeness to vary across firms. In this section, we first look at firm characteristics that affect a firm's ability to extract information from its stock price. We then consider firms that are financially constrained. Finally, we consider how the relation between SPI and TFP is affected by product market competition and corporate governance.

7.1. Firm characteristics

The effect of SPI on TFP should depend on firm characteristics. We consider four firm characteristics: firm size, firm age, complexity, and business risk. For each characteristic, we develop

predictions on how it affects the relation between SPI and TFP. Empirically, we test our hypotheses using the following specification:

$$TFP_{it} = \beta_0 + \beta_1 \cdot F_{it} \times SPI_{i,t-3,t-1} + \beta_2 \cdot SPI_{i,t-3,t-1} + \beta_3 \cdot F_{it} + X_{it} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}, \quad (17)$$

where i is the firm index, t is the year index, $SPI_{i,t-3,t-1}$ is the average of the previous three years of the measure of informativeness, and F stands for the firm characteristic we are investigating. X is the vector of control variables, Γ is the coefficient vector of the controls, μ_i is the firm fixed effect, ϑ_t is the year fixed effect, and ε_{it} is the error term. The results are reported in Table 12.

It is more difficult for larger firms to benefit from private information in stock prices. They are less able to adjust their organizational structure or production procedures. For example, a larger bureaucracy makes innovation more time-consuming, which in turn reduces the speed of productivity improvements (Holmstrom, 1989). We expect the TFP of large firms to be less sensitive to SPI, which corresponds to a negative β_1 in Eq. (17). The high asset dummy equals one if a firm's total assets exceed the yearly median and zero otherwise. Models 1 and 2 of Table 12 show the estimates. Both β_1s are negative and this coefficient is statistically significant at the 1% (10%) level for PIN (PSI). The results support our hypothesis that larger firms are less flexible and thus less able to take advantage of the information in their stock prices. However, it is important to note that the result that TFP increases with SPI holds for large firms so it is not a result driven by small firms. Specifically, if we exclude the bottom half of firms by either asset size or market value, we still find a relation between TFP and SPI (not tabulated).

Older firms are also at a disadvantage when it comes to using the private information in their stock prices. When firms become older, they are less able to adjust and take advantage of new growth opportunities (Loderer, Stulz, and Waelchli, 2016). This lower flexibility makes it more difficult for older firms to benefit from the private information in their stock price. We expect the TFP of older firms to be less sensitive to SPI so that β_1 should be negative. We measure a firm's age by the number of years after its first appearance on CRSP (e.g., Fama and French, 2001; Pastor and Veronesi, 2003; Loderer, Stulz, and Waelchli, 2016). The results are reported in Table 12. Models 3 and 4 of Table 12 show that the coefficients β_1 for the interaction terms (both PIN and PSI) are negative and statistically

significant at the 1% level. They confirm that older firms benefit less from the private information in their stock prices.

We expect the stock price to be less useful for more complex firms. We use firm-level diversification as an index of complexity. In stock markets, new information is incorporated into stock prices at the firm level, not at the business segment level. When a firm has more business segments, the information in its stock price is more difficult to interpret. When unique information on different business segments is aggregated, the information may not always be consistent or easy to interpret. Consequently, it is more challenging for managers to use the information in the firm's stock price to improve the performance of different segments. We expect the TFP of more diversified firms to be less sensitive to SPI. We measure diversification by a diversification dummy, Diversified, which equals one if a firm has more than one business segment and zero otherwise.[15] The results are reported in Table 12.

In Models 5 and 6, the coefficient of the diversification dummy, β_1, is negative and statistically significant at the 1% (10%) level for PIN (PSI). This indicates that diversified firms' productivity is less affected by their SPI, so diversification weakens the effect of SPI on TFP. This may be one reason why diversification hurts productivity.

Firms with risky businesses tend to rely less on the internal information and more on outside signals. We measure business risk by the standard deviation of daily stock returns during the previous year. As such, we expect the TFP of a riskier firm to be more sensitive to its SPI. Models 7 and 8 confirm the amplification effect of business risk. Both β_1s are positive and statistically significant at the 1% level. Riskier firms rely more on their SPI.

7.2. Financial constraints

Financially constrained firms have strong incentives to take steps to relax their constraints. Improving their resource allocation helps them in relaxing their constraints, as it improves their performance. At the same time, however, these firms are likely to be constrained in implementing

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[15] In unreported tests, we also use the number of segments as the measure for diversification, and the results are consistent.

changes that require funding.[16] Consequently, whether the productivity of financially constrained firms is more or less affected by SPI depends on whether making use of the information in the stock price requires the use of additional funds. As long as the information in the stock price can be used without additional funds, we expect the productivity of financially constrained firms to be more affected by SPI.

We use four different financial constraint measures that are widely used in the literature. They are a no-dividend dummy (which equals one if the firm does not pay a dividend and zero otherwise), the Whited-Wu index, an indicator variable for whether the firm has a bond rating (which equals one if the firm has no bond rating and zero otherwise), and the Kaplan and Zingales (1997) index. Our specification is as follows.

$$TFP_{it} = \beta_0 + \beta_1 \cdot FC_{it} \times SPI_{i,t-3,t-1} + \beta_2 \cdot SPI_{i,t-3,t-1} + \beta_3 \cdot FC_{it} + X_{it} \cdot \Gamma + \mu_i + \vartheta_t$$
$$+ \varepsilon_{it}, \tag{18}$$

where i is the firm index, t is the year index, $SPI_{i,t-3,t-1}$ stands for PIN or PSI, which is the average of the previous three years accordingly, FC stands for the measure of financial constraints, X is the vector of control variables, Γ is the coefficient vector of the controls, μ_i is the firm fixed effect, ϑ_t is the year fixed effect, and ε_{it} is the error term. We expect the coefficient of the interaction terms to be positive, which indicates an amplification effect of financial constraints. The results are reported in Table 13.

Table 13 estimates eight models for four measures of financial constraints. For each measure, we show results for PIN and PSI. The relevant interaction term, β_1, has a significant positive coefficient in each model except for Model 7. Among the eight models, the coefficients are statistically significant in seven models and insignificant at the 10% level in only one model. These results provide some evidence that financially constrained firms benefit more from the informativeness of their stock price.

7.3. Product market competition

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[16] Note that a higher SPI makes a firm more transparent to outside capital providers. Hence, a higher SPI could also relax financial constraints by making outsiders more willing to provide funds as they understand the firm better.

More competition in the product market gives firms a stronger motive to improve productivity so that they can survive or gain larger market share. We should therefore find that product market competition amplifies the effect of SPI on productivity.

We use three text-based network industry classification (TNIC) competition measures: TNIC Herfindahl-Hirschman Index (HHI) concentration, product similarity (Hoberg and Phillips, 2016), and product market fluidity (Hoberg, Phillips and Prabhala, 2014). These measures are from the Hoberg and Phillips data library. In our analysis, we define three dummy variables for high competition based on these three measures: Low HHI, High similarity, and High fluidity. High similarity (fluidity) equals one if the product similarity (fluidity) is above the yearly median and zero otherwise. Low HHI equals one if the TNIC HHI is below the yearly median and zero otherwise. Our specification is as follows:

$$TFP_{it} = \beta_0 + \beta_1 \cdot Competition_{it} \times SPI_{i,t-3,t-1} + \beta_2 \cdot SPI_{i,t-3,t-1} + \beta_3 \cdot Competition_{it}$$

$$+ X_{it} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}, \tag{19}$$

where i is the firm index, t is the year index, $SPI_{i,t-3,t-1}$ is the three-year average of the informativeness measure, Competition stands for the product market competition measure, X is the vector of control variables, Γ is the coefficient vector of the controls, μ_i is the firm fixed effect, ϑ_t is the year fixed effect, and ε_{it} is the error term. We expect the coefficient of the interaction term (β_1) to be positive, which indicates that firms in more competitive product markets are more likely to use their informative stock prices to improve productivity. The results are reported in Table 14.

Models 1 and 2 provide estimates for the coefficients of Low HHI, which is a dummy for high competition. The coefficients β_1 in the first two models are positive and statistically significant at the 1% level. Model 1 (2) shows that for high competition firms, the effect of PIN (PSI) is amplified by 37% (43%) compared to the effect for low competition firms. Models 3 and 4 show estimates for the High similarity variable. The product market is more competitive if the products of the firms in the industry are close substitutes. High similarity is a dummy for high competition. The estimates of β_1 in these models are positive and statistically significant at the 5% or the 10% level. Lastly, Models 5 and 6 show estimates for the High fluidity variable. Fluidity measures the extent to which rivals present competitive threats to the firm. The coefficients β_1 for PIN and PSI are both positive but only

statistically significant at the 10% level for PSI in Model 6. These results are consistent with the results for the High similarity variable. All results in Table 14 are consistent with firms in more competitive product markets reacting to the information in their stock price more strongly, and accordingly, the SPI effect on TFP is amplified by product market competition.

7.4. Corporate governance

We would expect better governed firms to be more incentivized to make the most out of their resources. If a firm has weak governance, managers may shirk and ignore new information in the stock price. Therefore, we expect SPI to have more of an impact on TFP in firms with better governance.

Our corporate governance measures include a high institutional ownership dummy (based on median in a year), the number of blockholders (logarithm), and the G-index (Gompers, Ishii, and Metrick, 2003). Our regression model is as follows:

$$TFP_{it} = \beta_0 + \beta_1 \cdot Gov_{it} \times SPI_{i,t-3,t-1} + \beta_2 \cdot SPI_{i,t-3,t-1} + \beta_3 \cdot Gov_{it} + X_{it} \cdot \Gamma + \mu_i + \vartheta_t$$
$$+ \varepsilon_{it}, \tag{20}$$

where i is the firm index, t is the year index, $SPI_{i,t-3,t-1}$ stands for the three-year average of the informativeness measure, Gov stands for the corporate governance measure, X is the vector of control variables, Γ is the coefficient vector for the controls, μ_i is the firm fixed effect, ϑ_t is the year fixed effect, and ε_{it} is the error term. We expect the coefficient of the interaction terms (β_1) to be negative for the SPI interaction with the G-index (weak governance), and positive for the SPI interaction with the remaining two measures. The results are reported in Table 15.

Models 1 and 2 show estimates for institutional ownership. It is common in the literature to view higher institutional ownership as indicating more monitoring from institutional investors and better external governance. We measure the strength of this governance by the High institutional ownership dummy, which equals one if institutional ownership is above the median in a year and zero otherwise. The coefficients of the interaction term in Models 1 and 2 are both positive and statistically significant at the 1% or 5% level. They indicate that the TFP of firms with better governance is more sensitive to SPI.

Models 3 and 4 show estimates for the number of blockholders (logarithm). A blockholder is a shareholder holding at least 5% of a firm's outstanding shares. Blockholders have strong incentives to monitor firms because they are less likely to be free riders than some shareholders with smaller holdings. More blockholders suggests stronger governance. The coefficient of the interaction between the number of blockholders and the informativeness measure is positive in both models, which confirms that firms with stronger governance have a stronger TFP-SPI sensitivity.

Our last governance measure is the G-index. A high value of the G-index indicates more entrenchment of managers and weaker governance. Models 5 and 6 show the results for the G-index. The coefficient of the interaction between the G-index and PIN, β_1, is negative and statistically significant at the 1% level. The coefficient of the interaction for PSI is also negative but not statistically different from zero. The evidence from all three measures of corporate governance consistently shows that TFP for firms with better governance is more sensitive to SPI.

8. Alternative efficiency measures

We now show that the relation between TFP and SPI holds for other efficiency measures. Following Loderer, Stulz, and Waelchli (2016), we use the following five efficiency measures: sales/book-value-of-assets ratio, sales/value-of-assets-in-place (VAIP) ratio, cost of goods sold (COGS) per employee, ROA, and the loss dummy for negative net income. We also include a TFP growth measure originally proposed by Chun, Kim, and Morck (2011).[17] The results for these tests are shown in Table 16.

Models 1 and 2 provide estimates using the sales/book-value-of-assets ratio as a dependent variable. The results show that PIN (PSI) has a positive coefficient, which is statistically significant at the 5% (1%) level. Models 3 and 4 show results with sales/value-of-assets-in-place ratio as the dependent variable. The results are consistent with those of Models 1 and 2. The results for the ratio of COGS per employee are shown in Models 5 and 6. The coefficient of PSI is negative and statistically significant at the 1% level. The coefficient of PIN is not significant at the conventional level. This is the only insignificant coefficient out of the ten in this table. Models 7 and 8 show results for ROA. Both PIN

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[17] The calculation of the TFP Growth measure is in Appendix C.

and PSI have positive coefficients that are significant at the 1% level. Models 9 and 10 report results for the loss dummy. Both PIN and PSI have negative coefficients that are significant at the 1% level. Lastly, Models 11 and 12 show the results for the effects of SPI on TFP Growth. Both PIN and PSI have positive coefficients that are statistically significant at the 1% level. The evidence for these alternative efficiency measures corroborates our earlier findings that SPI improves firms' efficiency.

9. Conclusion

Our paper provides evidence that an increase in the informativeness of a firm's stock price causes an increase in the firm's productivity. We address endogeneity concerns using multiple methods. Our baseline specification includes firm fixed effects to account for time-invariant unobserved firm-specific variables and uses lagged measures of informativeness. More importantly, we explore DiD analyses based on exogenous shocks to stock price informativeness. These efforts provide strong evidence in support of the causal effect of stock price informativeness on TFP. Using mutual fund flow pressure and brokerage firm closures as exogenous shocks to price informativeness, we further illustrate a concrete channel through which stock price informativeness affects firm productivity. Specifically, we show that firms' CEO turnover decisions are less sensitive to Tobin's q after firms experience fund flow pressure or a brokerage firm closure and a reduction in CEO turnover has an adverse impact on firm productivity. An increase in stock price informativeness could affect productivity through other channels than the one we use as an illustration, but we leave the investigation of additional channels to future work. For example, economic competitiveness could increase price informativeness (Irvine and Pontiff, 2009) and drive firms to increase innovation, which is typically considered a missing factor of production.

We further investigate predictions about how the impact of SPI on TFP varies along different firm characteristics. We predict and confirm that firm size, firm age, and firm complexity affect adversely the ability of the firm to exploit information in its stock price. We also find that financial constraints, product market competition, and better governance amplify the sensitivity of productivity to stock price informativeness.

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Our results have implications for the role of the stock market and the benefits of being a listed company. With our results, the price discovery function of the stock market plays an important role in how firms operate and how efficient they are. The role of the stock market is not just to provide funds to firms but to also guide their decisions. As a result, firms that benefit from that price discovery because their common stock is listed on an exchange can and do use it to make better decisions that makes them more productive.

Our analyses focus on US public firms, but our findings may have implications on cross-country differences in living standards. Solow (1956) links higher living standards to higher productivity growth. Our results imply that higher stock price informativeness in a country can be a contributing factor to the economic success of that country (Morck, Yeung, and Yu, 2013). As Morck, Yeung, and Yu (2000) show, cross-country variation in stock price informativeness can be partly explained by differences in the quality of institutions. Our results suggest that one reason better institutions lead countries to be more economically successful is that their higher stock price informativeness causes their firms to be more productive.

Appendix A. Variable definitions

Bond rating	a dummy variable equal to one if a firm has debt outstanding but does not have S&P long-term senior debt rating in or before that year or has default debt rating in that year and zero otherwise
Business risk	the standard deviation of the firm's daily stock returns over the previous year
Cash/Assets	cash and cash equivalent (CHE) scaled by total assets
Cash flow	the operating cash flow less investing cash flow and dividends scaled by total assets
COGS/Employees	the cost of goods sold (COGS) scaled by employees, as calculated in Loderer, Stulz, and Waelchli (2016)
Debt/Assets	the sum of short-term and long-term debt scaled by total assets
Diversified	a dummy variable equal to one if a firm has multiple segments and zero otherwise

Dividend dummy	a dummy variable equal to one if a firm pay a dividend and zero otherwise
Firm age	the number of years since a firm appeared in the CRSP database
G-index	the governance measure following Gompers, Ishii, and Metrick (2003)
Gamma	the average of the previous three years of the Gamma, where Gamma(Market) is from Frésard (2012) and Gamma(No market) is from Llorente et al. (2002)
High assets	a dummy variable equal to one if a firm has above yearly median total assets and zero otherwise
High fluidity	a dummy variable equal to one if a firm has above yearly median fluidity (a measure of product market competition), as defined in Hoberg, Phillips, and Prabhala (2014), and zero otherwise
High similarity	a dummy variable equal to one if a firm has above yearly median similarity (a measure of product market competition), as defined in Hoberg and Phillips (2016), and zero otherwise
High institutional ownership	a dummy variable equal to one if a firm's institutional ownership is above the median in a year and zero otherwise.
IQS	investment-q sensitivity: regress capital expenditures (scaled by total assets) on lagged Tobin's q, logarithm of total assets, and cash flows in a 5-year rolling window. IQS is the coefficient of Tobin's q
Kaplan-Zingales (KZ) index	the financial constraint index constructed following Kaplan and Zingales (1997)
Log(Assets)	the natural logarithm of total book value of assets
Log(N_blockholders)	the natural logarithm of the number of a firm's large shareholders (>5%)
Log(Cashflow)	the natural logarithm of cash flow
Log(Employees)	the natural logarithm of the number of employees
Log(Sales)	the natural logarithm of sales in the previous year

Log(Wages)	the natural logarithm of staff expenses
Loss	a dummy variable equal to one if a firm's net income is negative
Low HHI	a dummy variable equal to one if a firm has below yearly median firm-level Herfindahl/concentration measure, as calculated in Hoberg and Phillips (2016), and zero otherwise
MFFlow	a dummy variable that equals one if a stock's hypothetical fund sales is positive and zero otherwise, where the hypothetical fund sales follow that in Edmans, Goldstein, and Jiang (2012)
No-dividend dummy	a dummy variable equal to one if a firm does not pay a dividend and zero otherwise
Old CEO	a dummy variable equal to one if a CEO is older than 60
PIN	the average of the previous three years of PIN (probability of information-based trading) following Easley, Hvidkjaer, and O'Hara (2002)
PP&E/Assets	the value of plant, property, and equipment (PP&E) scaled by total assets
PSI	the average of the previous three years of PSI (Stock Price Nonsynchronicity) following Durnev, Morck, and Yeung (2004)
R&D/Assets	research & development (R&D) expenditures scaled by total assets, which is set to zero if missing
Return volatility	the standard deviation of the previous year's daily stock returns
ROA	return on assets – the ratio of the firm's operating income before depreciation divided by the lagged book value of total assets
ROE	return on equity – the ratio of the firm's net income scaled by shareholder (book value) equity
ROE volatility	the standard deviation of ROE over the previous five years
Sales/BV	a firm's sales scaled by book value as calculated in Loderer, Stulz, and Waelchli (2016)

Sales/VAIP   a firm's sales scaled by the value of assets in place (VAIP) as calculated in Loderer, Stulz, and Waelchli (2016)

SG&A   the natural logarithm of selling, general and administrative (SG&A) costs scaled by total assets

Turnover   a dummy variable that equals one if a firm has CEO turnover in a year and zero otherwise

TFP   total factor productivity calculated following Ackerberg, Caves, and Frazer (2015)

Tobin's q   the sum of total assets plus market value of equity minus book value of equity divided by total assets

Whited-Wu index   the financial constraint index constructed following Whited and Wu (2006)

Appendix B. TFP estimation

Our main measure of productivity is the TFP, which is the portion of output not explained by the amount of inputs used in production. TFP increases as a firm uses its inputs more efficiently. Consider the Cobb-Douglas product function

$$Y = A \cdot K^{\alpha} \cdot L^{\beta}, \tag{A1}$$

where Y is the output, K is capital, L is labor, and A is productivity.

Taking the natural logarithm on both sides, we have

$$\ln(Y) = \alpha \cdot \ln(K) + \beta \cdot \ln(L) + \ln(A). \tag{A2}$$

To calculate $\ln(A)$, the measure of TFP, we estimate the following specification

$$\ln(Y) = \beta_0 + \alpha \cdot \ln(K) + \beta \cdot \ln(L) + \varepsilon, \tag{A3}$$

where β_0 is the intercept and ε is the error term (residuals after the estimation). If we rearrange the terms on the right-hand side, we have

$$\ln(Y) = \alpha \cdot \ln(K) + \beta \cdot \ln(L) + \beta_0 + \varepsilon. \tag{A4}$$

Comparing Eq. (A2) and Eq. (A4), TFP can be measured as

$$\ln(A) = \beta_0 + \varepsilon \tag{A5}$$

so that TFP is the sum of the intercept and the residual in Eq. (A3), which is the part of output unexplained by inputs (capital K and labor L).

Rewriting Eq. (A3) and using lower letters for the log of variables in capital letters, we have

$$y_{i,t} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \epsilon_{it}, \tag{A6}$$

where $y_{i,t}$ is the log of the value added of the firm, k_{it} is the log value of capital, l_{it} is the log value of labor, and ϵ_{it} is the error term. Using hats to denote estimates, our TFP measure is calculated as $y_{i,t} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it}$.

To calculate TFP, we first need to estimate the production function Eq., i.e. the coefficients in Eq. (A6). Due to the endogeneity issue mentioned above, the OLS estimator is biased (Olley and Pakes, 1996; Levinsohn and Petrin, 2003). We estimate the production function following the method by

Ackerberg, Caves, and Frazer (2015). In our robustness tests, we try an alternative firm-level TFP measure, which is calculated by Imrohoroğlu, and Tüzel (2014) and is based on the methodology in Olley and Pakes (1996). Our results are robust to the alternative TFP measure.

To calculate firm-level TFP, we use firm data from Compustat. Besides the data from Compustat, we use the following additional data for the production function estimation: i) the price index for gross domestic product (GDP) as a deflator for the value added and ii) the price index for private fixed investment as a deflator for investment and capital (both from the BEA).

Value added is sales minus materials, deflated by the GDP deflator. Sales are revenue (revt) from Compustat. Materials is total expenses minus labor expenses. Total expenses is revenue less operating income before depreciation and amortization (oibdp). Labor expenses is the wage (xlr) variable in Compustat. When xlr is missing, we first calculate the average wage per employee within an industry (Fama-French 12) using the nonmissing wages in that industry, and then we calculate a firm's labor cost using the number of employees in the firm times the industry average wage per employee. Capital (K) is measured as gross plant, property, and equipment (ppegt) deflated by the price deflator for investment and then adjusted to take into account the average age of the capital stock (Hall, 1990; Brynjolfsson and Hitt, 2003). Labor (L) is the number of employees.

Appendix C. TFP growth estimation

We calculate a measure of firm-level TFP growth following the definition in Chun, Kim, and Morck (2011, 2016). Specifically, the TFP growth is defined as

$$\Delta\ln(TFP_{i,t}) = \Delta\ln(Y_{i,t}) - \frac{1}{2}\big[S_{L,i,t} + S_{L,i,t-1}\big]\Delta\ln(L_{i,t}) - \frac{1}{2}\big[S_{K,i,t} + S_{K,i,t-1}\big]\Delta\ln(K_{i,t}),$$

where $Y_{i,t}$, $L_{i,t}$, and $K_{i,t}$ are firm i's value-added, labor, and capital, respectively. Δ is the first-difference operator, and $\ln(\cdot)$ is the natural logarithm. $S_{L,i,t}$ and $S_{K,i,t}$ are the shares of the firm's labor costs and capital costs.

Value-added $Y_{i,t}$ is the operating income before depreciation (oibdp) plus labor. Labor is the wage expenses (xlr). When the wage expenses are missing, labor is calculated as the number of employees (emp) times the average wage per employee in the industry (SIC2), in which the wage per employee is calculated as xlr divided by emp for each firm in the industry. Capital is defined as gross plant, property, and equipment (ppegt). We account for inflation following the method of İmrohoroğlu and Tüzel (2014) and Brynjolfsson and Hitt (2003). Firm i's labor cost share, $S_{L,i,t}$, is its labor cost divided by the sum of its labor and capital costs. Firm i's capital cost share, $S_{K,i,t}$, is one minus its labor cost share. We follow the Bureau of Labor Statistics (BLS) method in smoothing $S_{L,i,t}$ and $S_{K,i,t}$ by averaging each across the current year and the previous year as shown in the equation.

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Fig. 1. Graphical analysis of the effect of brokerage closures on TFP

This figure shows the graphical analysis for the effect of brokerage closures on TFP. The y-axis plots the coefficient estimates from regressing TFP on dummy variables indicating the year relative to a brokerage closure, controlling for year fixed effects and firm size. The x-axis shows the time relative to the brokerage closure. The dashed lines correspond to 90% confidence intervals of the coefficient estimates, and the confidence intervals are based on standard errors clustered at the firm level. The sample includes firms that experienced brokerage closures and control firms matched by total assets and Tobin's q in the same industry (two-digit SIC code).
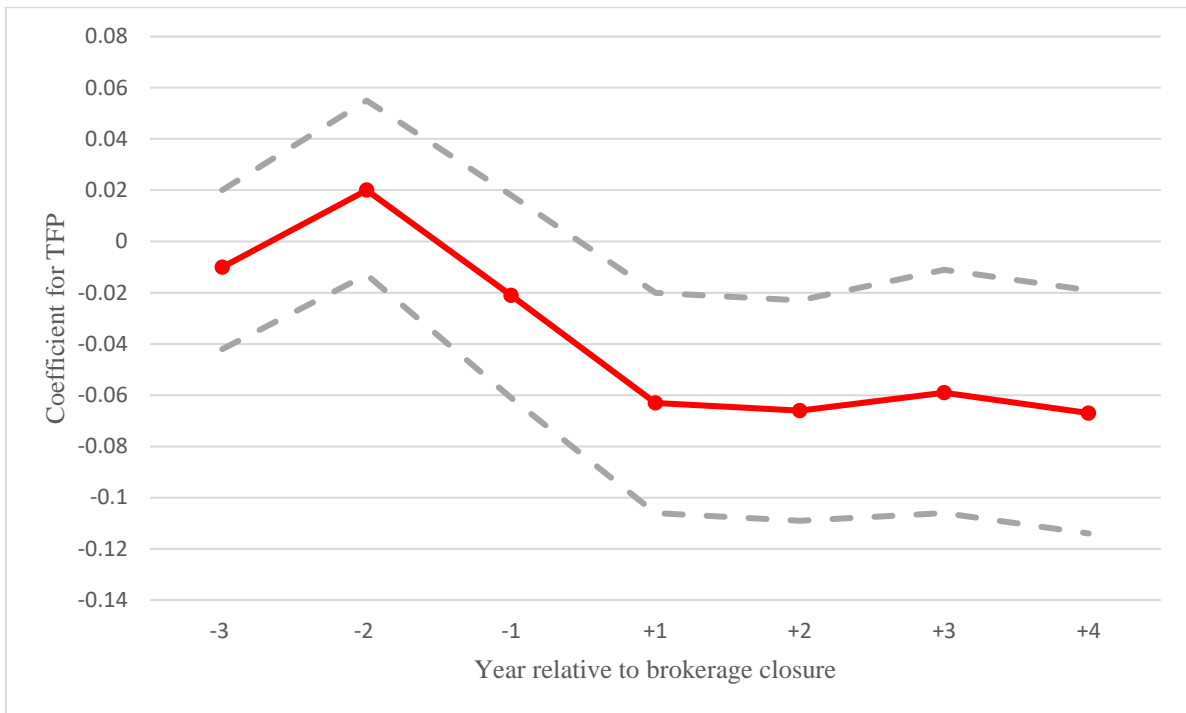
Fig. 2. Graphical analysis of the effect of S&P 500 index additions on TFP

This figure shows the graphical analysis for the effect of S&P 500 index additions on TFP. The y-axis plots the coefficient estimates from regressing TFP on dummy variables indicating the year relative to an index addition, controlling for year fixed effects and firm size. The x-axis shows the time relative to the index addition. The dashed lines correspond to 90% confidence intervals of the coefficient estimates, and the confidence intervals are based on standard errors clustered at the firm level. The sample includes firms that were added to the S&P 500 index and control firms matched by total assets and Tobin's q in the same industry (two-digit SIC code).
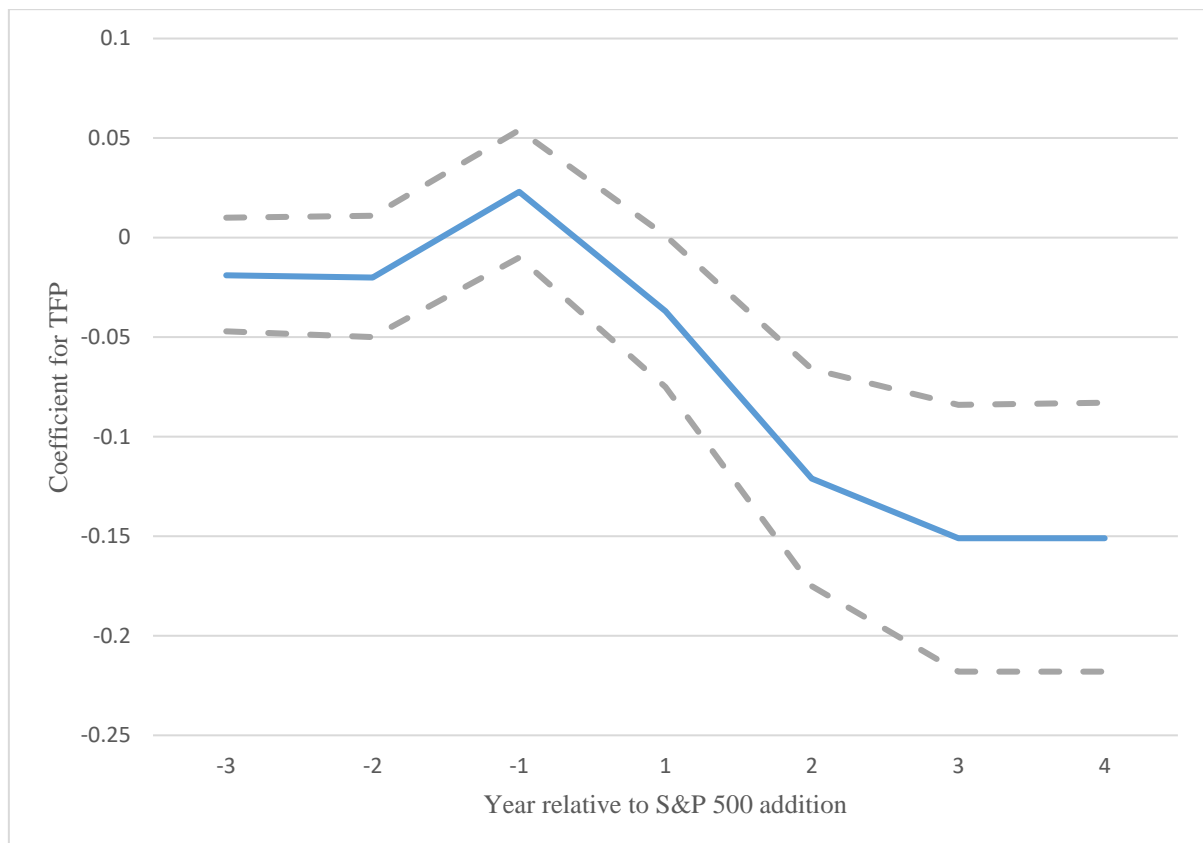
Table 1

Summary statistics

This table presents summary statistics for TFP, stock price informativeness measures PIN and PSI, and firm characteristics. The sample consists of firms in Compustat for which TFP and the stock price informativeness measures are available for the years 1994–2015, inclusive. All variables are winsorized at the 1st and 99th percentile values. Variable definitions are in Appendix A.

Variable	Mean	p25	p50	p75	SD	N
TFP	0.03	–0.33	0.00	0.37	0.60	66,341
PIN	0.22	0.14	0.20	0.28	0.11	66,341
PSI	2.22	0.90	2.06	3.44	1.71	63,504
Log(Assets)	6.55	5.08	6.43	7.88	2.00	66,341
Cash/Assets	0.14	0.02	0.08	0.21	0.17	66,341
Debt/Assets	0.24	0.05	0.21	0.36	0.22	66,134
R&D/Assets	0.03	0.00	0.00	0.03	0.06	66,341
Tobin's q	1.82	1.10	1.41	2.03	1.40	64,876
PP&E/Assets	0.28	0.09	0.21	0.42	0.23	66,341
Business risk	0.03	0.02	0.03	0.04	0.02	55,492
Log(N_blockholders)	1.06	0.68	1.10	1.39	0.55	25,511
Diversified	0.42	0	0	1	0.49	66,341
SG&A/Assets	0.25	0.07	0.19	0.35	0.25	66,341
G-index	8.94	7	9	11	2.74	19,796

Table 2

Price informativeness and productivity

This table presents panel regressions of total factor productivity (TFP) on stock price informativeness and other firm-level controls. In Panel A, stock price informativeness is measured by the probability of informed trading (PIN) and stock price nonsynchronicity (PSI). IQS is investment-q sensitivity. In Panel B, we test additional SPI measures. The first measure is Gamma, a trading-based informativeness measure calculated in Eq. (12) in Llorente et al. (2002). We calculate this measure in two ways. The first method (Columns 1 and 4) is as in Eq. (3) in Frésard (2012) and controls for both firm and market returns, while the second method (Columns 2 and 5) only controls for firm returns as in the original Llorente et al. (2002). The last additional stock price informativeness measure, Adjusted PIN (APIN), is calculated using Eq. (7) in Duarte and Young (2009). In our regressions, we use the average SPI over the previous three years. All specifications include firm and year fixed effects. The sample consists of firms in Compustat for which TFP and the stock price informativeness measures are available for the years 1994–2015 except for Column 5 in Panel A, which is from 1962–2015. Robust standard errors are clustered at the firm level. Variable definitions are in Appendix A. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Primary SPI measures (PIN & PSI)

Variables	(1) TFP	(2) TFP	(3) TFP	(4) TFP	(5) TFP	(6) TFP	(7) TFP
PIN	0.262***		0.256***			0.234***	
	[8.80]		[8.63]			[7.82]	
PSI		0.018***		0.019***	0.010***		0.020***
		[5.92]		[6.31]	[3.82]		[6.50]
Log(Assets)	0.235***	0.238***	0.225***	0.228***	0.170***	0.221***	0.225***
	[35.75]	[34.41]	[33.39]	[32.15]	[30.02]	[31.49]	[30.50]
Tobin's q	0.079***	0.079***	0.077***	0.078***	0.136***	0.073***	0.074***
	[19.63]	[19.34]	[19.30]	[19.03]	[43.68]	[17.11]	[16.83]
Cash/Assets			0.042	0.043	-0.049*	0.067**	0.070**
			[1.54]	[1.52]	[-1.85]	[2.30]	[2.33]
Debt/Assets			–0.226***	–0.233***	–0.278***	–0.214***	–0.220***
			[–10.80]	[–10.88]	[–14.83]	[–9.91]	[–9.95]
R&D/Assets			–1.139***	–1.137***	–1.943***	–1.153***	–1.145***
			[–9.78]	[–9.72]	[–15.84]	[–9.13]	[–9.04]
Capex/Assets						0.658***	0.670***
						[9.90]	[10.05]
IQS						–0.008*	–0.009**
						[–1.90]	[–2.18]
Capex/Assets * IQS						0.060	0.074*
						[1.43]	[1.74]
Observations	61,554	58,889	61,363	58,700	108,832	60,121	57,497
R-squared	0.178	0.176	0.192	0.191	0.172	0.172	0.172
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y

Panel B: Additional SPI measures (Gamma and APIN)

Variables	(1) TFP	(2) TFP	(3) TFP	(4) TFP	(5) TFP	(6) TFP
Gamma (Market)	0.035*** [2.65]			0.031** [2.35]		
Gamma (No market)		0.028** [2.32]			0.024** [2.05]	
APIN			0.177*** [5.55]			0.175*** [5.55]
Log(Assets)	0.226*** [33.23]	0.226*** [33.22]	0.244*** [34.55]	0.217*** [31.50]	0.217*** [31.50]	0.234*** [32.21]
Tobin's q	0.078*** [18.32]	0.078*** [18.32]	0.074*** [18.15]	0.077*** [18.08]	0.077*** [18.09]	0.072*** [17.84]
Cash/Assets				0.026 [0.90]	0.026 [0.90]	0.039 [1.34]
Debt/Assets				−0.256*** [−11.68]	−0.256*** [−11.69]	−0.259*** [−11.14]
R&D/Assets				−1.161*** [−9.39]	−1.161*** [−9.39]	−1.171*** [−9.23]
Observations	54,485	54,485	48,924	54,310	54,310	48,760
R-squared	0.174	0.174	0.179	0.190	0.190	0.195
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Table 3

The effect of brokerage house closures on stock price informativeness

This table shows the effect of brokerage closures on stock price informativeness. The specification is as follows: $SPI_{it} = \beta_0 + \beta_1 \cdot Closure_{it} + X_{i,t-1} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}$. SPI is PIN or PSI. Closure is a dummy variable that equals one if a stock is covered by a closed research department in the previous one or two years and zero otherwise. Control variables are the same as used in Column 3 of Table 2. The sample consists of firms in Compustat for which the stock price informativeness measures are available for the years 1994–2015. Firm and year fixed effects are included. Robust standard errors are clustered at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) PIN	(2) PSI
Closure	–0.013**	–0.101**
	[–2.48]	[–1.97]
Log(Assets)	–0.032***	–0.469***
	[–22.06]	[–25.04]
Tobin's q	–0.005***	–0.278***
	[–5.74]	[–34.37]
Cash/Assets	–0.008	–0.190**
	[–1.20]	[–2.51]
Debt/Assets	0.035***	0.784***
	[6.48]	[10.90]
R&D/Assets	–0.001	0.426*
	[–0.04]	[1.71]
Observations	44,359	42,257
R-squared	0.484	0.765
Firm FE	Y	Y
Year FE	Y	Y

Table 4

DiD analysis: brokerage house closures and productivity

This table shows DiD tests based on the closures of brokerage house research departments. The sample is from 1996 to 2011. A firm is defined as a treated firm if its stock is covered by a closed research department. For each closure event, we define an event window as four years before to four years after the closure. For each treated firm, we use propensity score match to choose a control firm in the same industry (two-digit SIC) and matched by total assets and Tobin's q using Mahalanobis distance. In Model 1 the treatment dummy Treatment_post equals one if a stock is covered by a closed research department and the year is between one and four years after the closure year and zero otherwise. In Model 2 we define four treatment dummy variables, one dummy for each year during the four years after a closure. Closure years are dropped in the regressions. All specifications include firm fixed effects and year fixed effects. Robust standard errors are clustered at the firm level. Variable definitions are in Appendix A. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) TFP	(2) TFP
Treatment_post	–0.043**	
	[–2.29]	
One year after closure		–0.051***
		[–2.75]
Two years after closure		–0.049**
		[–2.45]
Three years after closure		–0.040*
		[–1.80]
Four years after closure		–0.043*
		[–1.94]
Log(Assets)	0.248***	0.249***
	[12.88]	[12.98]
Tobin's q	0.035***	0.035***
	[3.85]	[3.85]
Cash/Assets	0.173**	0.173**
	[2.27]	[2.27]
Debt/Assets	–0.248***	–0.246***
	[–4.76]	[–4.71]
R&D/Assets	–1.364***	–1.361***
	[–3.23]	[–3.22]
Observations	7,851	7,851
R-squared	0.801	0.801
Firm FE	Y	Y
Year FE	Y	Y

Table 5

The effect of S&P 500 additions on stock price informativeness

This table shows the effect of S&P 500 additions on the stock price informativeness. The specification is as follows: $SPI_{it} = \beta_0 + \beta_1 \cdot \text{Addition}_{it} + X_{i,t-1} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}$. SPI is PIN or PSI. Addition is a dummy variable that equals one if a firm is added to the S&P 500 index in the previous one or two years and zero otherwise. Control variables are the same as used in Column 3 of Table 2. Firm and year fixed effects are included. The sample includes firms with above yearly median book assets because firms added into S&P 500 index are unlikely to have assets below median assets. Robust standard errors are clustered at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) PIN	(2) PSI
Addition	–0.008*	–0.154***
	[–1.66]	[–3.31]
Log(Assets)	–0.019***	–0.297***
	[–9.80]	[–10.45]
Tobin's q	–0.002**	–0.106***
	[–2.17]	[–5.21]
Cash/Assets	–0.011	–0.275**
	[–1.28]	[–2.53]
Debt/Assets	0.041***	0.848***
	[4.91]	[6.93]
R&D/Assets	0.001	0.220
	[0.02]	[0.47]
Observations	21,830	20,913
R-squared	0.356	0.726
Firm FE	Y	Y
Year FE	Y	Y

Table 6

DiD analysis: S&P 500 index additions and productivity

This table shows DiD tests based on S&P 500 index additions. A firm is defined as a treated firm if it is added to the S&P 500 index in a year. For each index addition, we define an event window as four years before to four years after the index addition. For each treated firm, we use PSM to choose a control firm in the same industry (two-digit SIC) and matched by total assets and Tobin's q with minimum Mahalanobis distance in Models 1, 4, 5, and 6. We use additional match variable lagged stock return in Model 2 or lagged TFP in Model 3. In Models 1 to 5 the treatment dummy, SP500_addition, equals one if a firm is added to the S&P 500 index over the previous four years and zero otherwise. In Model 6 we define four treatment dummy variables, one dummy for each year during the four years after a closure. All specifications include firm and year fixed effects. Robust standard errors are clustered at the firm level. Variable definitions are in Appendix A. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) TFP	(2) TFP	(3) TFP	(4) TFP	(5) TFP	(6) TFP
SP500_addition	–0.083***	–0.100***	–0.082***	–0.084***	–0.058**	
	[–3.81]	[–4.78]	[–4.00]	[–3.77]	[–2.16]	
One year after add						–0.036*
						[–1.86]
Two years after add						–0.105***
						[–3.87]
Three years after add						–0.141***
						[–4.42]
Four years after add						–0.146***
						[–4.44]
Log(Assets)	0.167***	0.208***	0.195***	0.192***	0.197***	0.183***
	[7.26]	[8.31]	[9.64]	[7.22]	[5.94]	[7.43]
Tobin's q	0.049***	0.052***	0.057***	0.043***	0.060***	0.066***
	[6.38]	[5.11]	[6.82]	[6.01]	[4.66]	[6.18]
Cash/Assets	–0.025	0.080	0.138	–0.035	–0.085	–0.077
	[–0.24]	[0.71]	[1.34]	[–0.27]	[–0.62]	[–0.68]
Debt/Assets	–0.288***	–0.253***	–0.302***	–0.248***	–0.232**	–0.243***
	[–3.57]	[–2.97]	[–4.85]	[–3.15]	[–2.56]	[–2.83]
R&D/Assets	–1.207**	–1.086**	–0.980*	–0.690	–0.433	–1.047**
	[–2.28]	[–2.26]	[–1.92]	[–1.30]	[–1.00]	[–2.01]
Amihud				–0.098***	–1.453***	
				[–2.65]	[–6.64]	
Stock return				0.017	–0.009	
				[1.03]	[–0.59]	
Inst ownership					0.071	
					[0.73]	
Observations	3,908	3,855	3,887	3,202	2,141	3,482
R-squared	0.193	0.210	0.230	0.176	0.178	0.191
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Table 7

Mutual fund flow pressure and stock price informativeness

This table presents the estimates of the specification $SPI_{it} = \beta_0 + \beta_1 \cdot MFFlow_{i,t-1} + X_{i,t-1} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}$. SPI is PIN or PSI. MFFlow is a dummy variable that equals one if a stock's hypothetical fund sales is positive and zero otherwise. The hypothetical fund sales are constructed as in Edmans, Goldstein, and Jiang (2012). The sample consists of firms in Compustat for which the stock price informativeness measures are available for the years 1994–2015. Firm fixed effects and year fixed effects are included. Robust standard errors are clustered at the firm level. Variable definitions are in Appendix A. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) PIN	(2) PSI
MFFlow	–0.005***	–0.137***
	[–3.75]	[–8.67]
Log(Assets)	–0.032***	–0.439***
	[–21.92]	[–22.82]
Tobin's q	–0.005***	–0.136***
	[–5.72]	[–7.13]
Cash/Assets	–0.007	–0.341***
	[–1.16]	[–4.25]
Debt/Assets	0.034***	0.840***
	[6.37]	[10.93]
R&D/Assets	–0.001	0.400
	[–0.05]	[1.53]
Observations	44,359	42,257
R-squared	0.484	0.760
Firm FE	Y	Y
Year FE	Y	Y

Table 8

Mutual fund redemption pressure and TFP

This table shows the effect of mutual fund redemption on TFP. The specification is $TFP_{it} = \beta_0 + \beta_1 \cdot MFFlow_{i,t-1} + X_{it} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}$. MFFlow is a dummy variable that equals one if a stock's hypothetical fund sales is positive and zero otherwise. The hypothetical fund sales follow that in Edmans, Goldstein, and Jiang (2012). The sample consists of firms in Compustat for which our TFP variable is available for the years 1994–2015. Firm fixed effects and year fixed effects are controlled. Robust standard errors are clustered at the firm level. Variable definitions are in Appendix A. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) TFP	(2) TFP
MFFlow	–0.012***	–0.013***
	[–2.93]	[–3.15]
Log(Assets)	0.217***	0.209***
	[36.11]	[33.92]
Tobin's q	0.128***	0.126***
	[42.33]	[42.00]
Debt/Assets		–0.207***
		[–10.95]
Cash/Assets		0.018
		[0.69]
R&D/Assets		–1.196***
		[–10.85]
Observations	67,572	67,364
R-squared	0.791	0.794
Firm FE	Y	Y
Year FE	Y	Y

Table 9

Exogenous shocks to price informativness and CEO turnover

This table illustrates how decreases in stock price informativeness affect CEO turnover sensitivity to q. Panel A (B) presents the estimates of the logit model, where mutual fund flow pressure (brokerage house closure) is the exogenous shock to price informativeness. Turnover is a dummy variable that equals one if a firm experiences a CEO turnover in the year and zero otherwise. In Panel A, MFFlow is a dummy variable that equals one if a stock's hypothetical fund sales is positive and zero otherwise. The hypothetical fund sales are constructed as in Edmans, Goldstein, and Jiang (2012). The sample consists of firms in Execucomp for the years 1994–2015. In Panel B, Closure_post is a dummy variable that equals one if a firm experienced a brokerage closure in the previous four years and zero otherwise. In Panel B, we use the window [-4, 4] around brokerage closures and use a PSM sample as in Table 4 for which Execucomp data is available. *Old CEO* is a dummy variable that equals one if a CEO's age is above 60 and zero otherwise. Industry fixed effects and year fixed effects are included, where industry classification is the one-digit SIC. Robust standard errors are clustered at the firm level. Variable definitions are in Appendix A. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: CEO turnover sensitivity to q and mutual fund flow pressure

Variables	(1) CEO turnover	(2) CEO turnover
MFFlow × Tobin's q	0.130***	0.126***
	[2.80]	[2.84]
Tobin's q	–0.211***	–0.078**
	[–5.40]	[–2.01]
MFFlow	–0.353***	–0.347***
	[–3.68]	[–3.74]
Log(Assets)	0.086***	0.082***
	[5.02]	[4.69]
Return volatility	8.545***	3.253
	[4.21]	[1.43]
ROA		–3.787***
		[–13.77]
Debt/Assets		–0.368**
		[–2.46]
Old CEO		0.862***
		[19.20]
Observations	21,148	20,691
R-squared	0.0110	0.0461
Industry FE	Y	Y
Year FE	Y	Y

Panel B: CEO turnover sensitivity to q and brokerage research department closures

Variables	(1) CEO turnover	(2) CEO turnover
Tobin's q × Closure_post	0.255*	0.270**
	[1.86]	[1.98]
Tobin's q	–0.236***	–0.168**
	[–3.57]	[–2.25]
Closure_post	–0.423	–0.432
	[–1.34]	[–1.36]
Log(Assets)	0.044	0.062
	[1.00]	[1.39]
Volatility	5.009	–0.005
	[1.01]	[–0.00]
ROA		–2.068***
		[–3.03]
Debt/Assets		–0.270
		[–0.73]
Old CEO		0.006
		[0.05]
Observations	3,410	3,371
R-squared	0.0132	0.0177
Industry FE	Y	Y
Year FE	Y	Y

Table 10

CEO turnover and improvements of TFP

This table presents the estimates for the specification $\Delta TFP_{it} = \beta_0 + \beta_1 \cdot Turnover_{t-1} + \beta_2 \cdot Turnover_{i,t-2} + X_{i,t} \cdot \Gamma + \mu_j + \vartheta_t + \varepsilon_{it}$. Δ is the first-difference operator. Turnover is a dummy variable that equals one if a firm experiences a CEO turnover in the year and zero otherwise. In Model 2 we further include a Turnover dummy for the year $t - 3$. The sample consists of firms in the sample of Table 4, for which Execucomp data are available. Firm fixed effects and year fixed effects are controlled. Robust standard errors are clustered at the firm level. Variable definitions are in Appendix A. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) ΔTFP	(2) ΔTFP
Turnover$_{t-1}$	0.006	0.006
	[1.08]	[1.01]
Turnover$_{t-2}$	0.013**	0.012**
	[2.39]	[1.98]
Turnover$_{t-3}$		0.004
		[0.62]
Log(Assets)	–0.013**	–0.008
	[–2.57]	[–1.61]
Tobin's q	0.039***	0.047***
	[13.87]	[15.86]
Cash/Assets	0.084***	0.081**
	[2.85]	[2.50]
Debt/Assets	–0.023	–0.022
	[–1.40]	[–1.27]
R&D/Assets	–0.721***	–0.660***
	[–4.46]	[–3.93]
Observations	22,537	19,858
R-squared	0.081	0.082
Firm FE	Y	Y
Year FE	Y	Y

Table 11

Outputs, inputs, and TFP improvements

This table presents panel regressions of revenue, operating, and labor expenses on stock price informativeness and other firm-level controls. The operating cost is measured by SG&A (scaled by total assets), and the labor cost is measures by the wage expenses (xlr in Compustat). Stock price informativeness is measured by the probability of information-based trading (PIN) and stock price nonsynchronicity (PSI). In our regressions, we use the average PIN or PSI over the previous three years. The sample consists of firms in Compustat for which the stock price informativeness measures are available for the years 1994–2015. All specifications include firm and year fixed effects. Robust standard errors are clustered at the firm level. Variable definitions are in Appendix A. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) Log(Revenue)	(2) Log(Revenue)	(3) SG&A	(4) SG&A	(5) Log(LaborCost)	(6) Log(LaborCost)
PIN	0.042***		−0.026***		−0.295***	
	[2.93]		[−3.89]		[−3.77]	
PSI		0.009***		−0.002**		−0.018*
		[6.24]		[−2.34]		[−1.91]
Log(Assets)	0.410***	0.418***	−0.004*	−0.004**	0.633***	0.635***
	[56.46]	[56.23]	[−1.67]	[−1.96]	[27.85]	[25.71]
Tobin's q	0.035***	0.036***	−0.009***	−0.009***	−0.006	−0.007
	[19.00]	[18.79]	[−11.50]	[−11.42]	[−0.72]	[−0.88]
Cash/Assets	−0.321***	−0.329***	0.027***	0.031***	−0.18	−0.241*
	[−18.10]	[−18.35]	[3.46]	[3.91]	[−1.43]	[−1.92]
Debt/Assets	−0.086***	−0.088***	0.012***	0.012***	−0.186***	−0.219***
	[−7.92]	[−7.89]	[2.86]	[2.81]	[−2.73]	[−3.25]
R&D/Assets	0.593***	0.605***	0.465***	0.467***	3.683***	3.681***
	[10.81]	[10.94]	[13.45]	[13.37]	[5.03]	[4.94]
PP&E/Assets	−0.094***	−0.104***	0.011	0.015	0.452***	0.426***
	[−3.77]	[−4.02]	[1.20]	[1.49]	[3.52]	[3.23]
Log(Revenue(t-1))	0.498***	0.494***	−0.017***	−0.017***		
	[55.61]	[54.02]	[−7.35]	[−7.00]		
Observations	63,739	60,953	63,739	60,953	7,603	7,347
R-squared	0.889	0.889	0.077	0.079	0.663	0.661
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Table 12

Firm characteristics, price informativeness, and productivity

This table presents estimates of panel regressions of TFP on the interactions of firm characteristics and stock price informativeness and other firm level control variables. The dependent variable in all specifications is TFP. Stock price informativeness is measured by the probability of information-based trading (PIN) and stock price nonsynchronicity (PSI). In our regressions, we use the average PIN or PSI over the previous three years. The sample consists of firms in Compustat for which the stock price informativeness measures are available for the years 1994–2015. All controls used in Columns 3 and 4 of Table 3 are included, but for brevity their coefficients are not displayed. All specifications include firm and year fixed effects. Robust standard errors are clustered at the firm level. Variable definitions are in Appendix A. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm characteristic	High assets		Firm age		Diversified		Business risk	
Firm characteristic x PIN	–0.167***		–0.013***		–0.144***		5.950***	
	[–3.25]		[–6.25]		[–2.85]		[4.22]	
Firm characteristic x PSI		–0.008*		–0.001***		–0.007*		0.580***
		[–1.88]		[–5.38]		[–1.88]		[5.51]
PIN	0.335***		0.453***		0.298***		0.089*	
	[8.42]		[9.98]		[7.66]		[1.68]	
PSI		0.022***		0.034***		0.023***		0.001
		[6.47]		[8.34]		[6.57]		[0.16]
Firm characteristic	0.058***	0.035**	–0.002**	–0.003***	–0.002	–0.017	–3.568***	–3.663***
	[3.74]	[2.44]	[–2.15]	[–2.77]	[–0.16]	[–1.39]	[–8.57]	[–9.86]
Observations	61,363	58,700	61,045	58,402	47,428	45,620	51,377	49,212
R-squared	0.193	0.191	0.195	0.194	0.204	0.202	0.200	0.199
Other controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Table 13

Financial constraints, price informativeness, and productivity

This table presents estimates of panel regressions of TFP on the interactions of financial constraint measures and stock price informativeness and other firm-level control variables. We use four financial constraint measures: no-dividend dummy, Whited and Wu index, no bond rating dummy, and Kaplan-Zingales index. The dependent variable in all specifications is TFP. Stock price informativeness is measured by the probability of information-based trading (PIN) and stock price nonsynchronicity (PSI). In our regressions, we use the average PIN or PSI over the previous three years. The sample consists of firms in Compustat for which the stock price informativeness measures are available for the years 1994–2015. All controls used in Columns 3 and 4 of Table 2 (Panel A) are included, but for brevity their coefficients are not displayed. All specifications include firm and year fixed effects. Robust standard errors are clustered at the firm level. Variable definitions are in Appendix A. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fin. constraint	No dividend		WW index		Bond rating		KZ index	
PIN x Fin. const.	0.119***		0.705***		0.108**		0.005	
	[2.66]		[3.05]		[2.18]		[0.31]	
PSI x Fin. const.		0.010***		0.043**		0.008*		0.002*
		[3.02]		[2.07]		[1.73]		[1.89]
PIN	0.151***		0.381***		0.145***		0.214***	
	[4.26]		[4.90]		[3.86]		[7.54]	
PSI		0.009**		0.023***		0.010**		0.017***
		[2.56]		[3.63]		[2.44]		[5.62]
Fin. const.	–0.010	–0.006	1.122***	1.244***	0.017	0.025	–0.022***	–0.026***
	[–0.77]	[–0.54]	[12.69]	[14.01]	[1.05]	[1.60]	[–5.06]	[–6.64]
Observations	57,394	54,834	56,774	54,229	50,783	48,497	52,524	50,119
R-squared	0.205	0.204	0.219	0.213	0.198	0.197	0.215	0.215
Other controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Table 14

Product market competition, stock price informativeness, and productivity

This table presents estimates of panel regressions of TFP on the interactions of product market competition measures and stock price informativeness and other firm level control variables. Product market competition is measured by product similarity, product market fluidity, and TNIC HHI. The text-based network industry classification is used to construct these measures, which are available at the Hoberg-Phillips Data Library. In the tests, dummy variables for high competition are defined based on these competition measures: High similarity, High fluidity, and Low HHI, which are based on the median of the relevant measures in a year. The dependent variable in all specifications is TFP. Stock price informativeness is measured by the probability of information-based trading (PIN) and stock price nonsynchronicity (PSI). In our regressions, we use the average PIN or PSI over the previous three years. The sample consists of firms in Compustat for which the stock price informativeness measures are available for the years 1994–2015. All controls used in Columns 3 and 4 of Table 2 (Panel A) are included, but for brevity their coefficients are not displayed. All specifications include firm and year fixed effects. Robust standard errors are clustered at the firm level. Variable definitions are in Appendix A. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Competition Measure	Low HHI		High similarity		High fluidity	
Competition x PIN	0.111***		0.091*		0.044	
	[2.81]		[1.75]		[0.87]	
Competition x PSI		0.010***		0.008**		0.006*
		[3.31]		[1.97]		[1.69]
PIN	0.301***		0.319***		0.336***	
	[8.98]		[9.20]		[9.83]	
PSI		0.023***		0.025***		0.026***
		[7.22]		[7.77]		[8.27]
Competition	–0.022**	–0.017**	–0.027**	–0.022**	–0.036***	–0.036***
	[–2.26]	[–2.41]	[–2.14]	[–2.19]	[–3.17]	[–4.15]
Observations	46,848	44,780	46,848	44,780	43,421	41,490
R-squared	0.363	0.360	0.362	0.360	0.371	0.368
Other controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Table 15

Corporate governance and the role of stock price informativeness

This table presents estimates of panel regressions of TFP on the interactions of corporate governance measures and stock price informativeness and other firm-level control variables. The strength of corporate governance is measured by a high institutional ownership dummy (based on median in a year), the number of blockholders (logarithm), and the G-index (Gompers, Ishii, and Metrick, 2003). The dependent variable in all specifications is TFP. Stock price informativeness is measured by the probability of information-based trading (PIN) and stock price nonsynchronicity (PSI). In our regressions, we use the average PIN or PSI over the previous three years. The sample consists of firms in Compustat for which the stock price informativeness measures and the governance measures are available for the years 1994–2015. All controls used in Columns 3 and 4 of Table 2 (Panel A) are included, but for brevity their coefficients are not displayed. All specifications include firm and year fixed effects. Robust standard errors are clustered at the firm level. Variable definitions are in Appendix A. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Governance measure	High inst. ownership		Log(N_blockholders)		G-index	
Governance x PIN	0.147**		0.138**		–0.051***	
	[2.15]		[2.18]		[–3.62]	
Governance x PSI		0.020***		0.016***		–0.000
		[3.89]		[3.62]		[–0.30]
PIN	0.160***		0.080		0.597***	
	[2.73]		[1.00]		[4.22]	
PSI		0.016**		0.006		0.012
		[2.56]		[0.87]		[0.78]
Governance	–0.005	–0.003	–0.062***	–0.058***	0.001	–0.009
	[–0.37]	[–0.31]	[–4.96]	[–6.66]	[0.17]	[–1.49]
Observations	22,286	21,229	22,286	21,229	15,328	14,817
R-squared	0.224	0.223	0.226	0.224	0.214	0.211
Other controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Table 16

Alternative efficiency measures

This table presents panel regressions of different measures of productivity/efficiency on stock price informativeness and other firm-level controls. The measures of productivity/efficiency in Columns 1 to 10 are from Loderer, Stulz, and Waelchli (2016). TFP Growth (TFP Gr) in Columns 11 and 12 is from Chun, Kim, and Morck (2011). Stock price informativeness is measured by the probability of information-based trading (PIN) and stock price nonsynchronicity (PSI). In our regressions, we use the average PIN or PSI across the previous three years. The sample consists of firms in Compustat for which the stock price informativeness measures are available for the years 1994–2015. All specifications include firm and year fixed effects. Robust standard errors are clustered at the firm level. Variable definitions are in Appendix A. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) Sales/BV	(2) Sales/BV	(3) Sales/VAIP	(4) Sales/VAIP	(5) COGS/Emp	(6) COGS/Emp	(7) ROA	(8) ROA	(9) Loss	(10) Loss	(11) TFP Gr	(12) TFP Gr
PIN	0.043**		0.203*		4.738		0.055***		−0.581***		0.088***	
	[2.07]		[1.90]		[0.67]		[5.77]		[−2.97]		[3.16]	
PSI		0.012***		0.074***		−1.769***		0.009***		−0.136***		0.026***
		[5.55]		[4.27]		[−2.62]		[9.26]		[−7.62]		[8.00]
Log(Assets)	−0.550***	−0.532***	−0.971***	−0.866***	55.509***	54.090***	0.022***	0.028***	−0.477***	−0.538***	0.153***	0.157***
	[−50.59]	[−49.39]	[−26.58]	[−15.42]	[21.19]	[19.94]	[6.74]	[10.76]	[−15.91]	[−16.78]	[14.30]	[14.25]
Tobin's q	0.013***	0.014***	−0.007	−0.029***	2.887***	2.837***	0.011*	0.018***	−0.686***	−0.676***	0.037***	0.037***
	[7.62]	[7.93]	[−1.07]	[−2.77]	[7.13]	[6.99]	[1.73]	[15.26]	[−28.46]	[−27.80]	[10.67]	[10.44]
Cash/Assets	−0.397***	−0.397***	−1.135***	−1.286***	−19.307***	−20.782***	0.079***	0.071***	−1.734***	−1.743***	0.296***	0.288***
	[−19.65]	[−19.83]	[−12.47]	[−9.16]	[−3.32]	[−3.49]	[5.33]	[6.89]	[−11.01]	[−10.86]	[9.82]	[9.28]
Debt/Assets	−0.067***	−0.064***	1.245***	0.433**	−18.142***	−17.451***	−0.243***	−0.249***	4.054***	4.089***	−0.313***	−0.315***
	[−3.64]	[−3.54]	[9.21]	[2.12]	[−4.01]	[−3.76]	[−12.25]	[−11.90]	[34.04]	[33.32]	[−12.77]	[−12.36]
R&D/Assets	0.652***	0.691***	1.209***	0.898	58.200***	55.236***	−0.793***	−0.796***	15.034***	14.831***	−1.880***	−1.866***
	[8.37]	[8.82]	[2.72]	[1.19]	[2.78]	[2.63]	[−14.62]	[−14.90]	[23.12]	[22.69]	[−9.52]	[−9.41]
Cash flows	0.946***	0.944***	−2.873***	−2.412***								
	[30.47]	[30.16]	[−15.63]	[−7.85]								
Log(Sales), lag	0.442***	0.433***	0.864***	0.880***								
	[38.60]	[37.73]	[24.42]	[16.30]								
Log(Employees)					−113.898***	−112.793***						
					[−26.24]	[−25.48]						
Observations	63,739	60,955	63,739	60,955	63,740	60,956	63,740	60,956	43,480	41,413	53,458	50,959
R-squared	0.47	0.466	0.108	0.034	0.288	0.284	0.102	0.152	0.152	0.154	0.069	0.071
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y