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Does the Stock Market Make Firms More Productive?
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ABSTRACT

We test the hypothesis that greater stock price informativeness (SPI) leads to higher firm-level productivity (TFP). Management, directly or indirectly, learns more from more informative stock prices, so that more informative stock prices should make firms more productive. We find a positive relation between SPI and TFP. The relation is stronger for smaller, younger, riskier, less capital-intensive, and financially-constrained firms. Product market competition and better governance amplify the relation, while diversification weakens it. We address endogeneity concerns with fixed effects, instrumental variables, and the use of brokerage house research department closures and S&P 500 additions 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, and 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 U.S. firms to investigate whether better price discovery makes firms more productive. We find that it does. In other words, firms are more productive when the market for their stock leads to better price discovery.

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 learns nothing from price moves that it 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, and Kyle, 1985). The contention and evidence in the literature is that this information is valuable to management in guiding its 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. For example, corporate managers can learn from the information in stock prices for M&A decisions: if a firm's stock price drops after an M&A announcement, the manager may cancel the M&A plan (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). Bond, Goldstein, and Edmans (2012) review the theoretical and empirical literature on the real effects of price discovery.

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, and Durnev, Morck, and Yeung, 2004).

We use as our main measure of productivity Total Factor Productivity or TFP. TFP measures the overall effectiveness and efficiency with which capital and labor are used in the production process. To measure TFP, we have to estimate a production function with data available from Compustat. To do so, we follow Levinsohn and Petrin (2003) and Ackerberg, Caves, and Frazer (2015). We also use other measures of firm efficiency that are used in the corporate finance literature. We show that these measures are also positively related to SPI, so that our conclusions do not depend on the use of TFP.

We find that the evidence supports our hypothesis that firms with better price discovery in the stock market are more productive. Such a result could be explained by factors that influence both price discovery and firm productivity. To make a causal interpretation of our results plausible, we address potential endogeneity concerns in multiple ways. First, we use instrumental variables for SPI. Second, we provide difference in differences estimations using exogenous shocks to SPI. Third, we use quasi-natural experiments of changes in price informativeness of stocks. The first experiment involves closures of analyst research departments and the second experiment uses additions to the S&P500 index. Fourth, we control for firm fixed effects to minimize the possibility that a firm-invariant omitted variable is affecting our results. Fifth, 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.

One of our approaches to deal with endogeneity has important implications on its own. For a firm, being added to the S&P 500 is viewed as an exogenous event as firms cannot directly get themselves included and S&P makes it clear that inclusion has no information about a firm's future performance. We examine the impact on firm productivity of being added to the S&P 500. Being added to the index decreases SPI as it is known that being added to the index increases the correlation of a stock with the index. Hence, we would expect that being added to the index decreases a firm's productivity. Our evidence is strongly supportive of this prediction.

To understand how SPI affects TFP, we first examine the channels through which SPI affects TFP. We find that firms with more informative stock prices have higher revenues, lower operating costs (SG&A), and lower labor expenses. The higher revenues and lower costs help improve productivity.

We expect the strength of the relation between SPI and TFP to vary depending on firm characteristics. First, we would expect the relation to 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 Walchli, 2016). We find that this is indeed the case. The literature cited earlier implies that firms learn about acquisitions through their stock price. Hence, we would expect acquisitive firms to benefit more from a more informative stock price. Again, we find support for this hypothesis.

With more complex firms, investors and managers are expected to find it more difficult to extract information from the stock price. 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. Within a firm, labor is generally more easily reallocated among different projects than capital. For example, capital (e.g. machines and other equipment) generally has a specific function (in a specific business line) that is difficult to change. But employees (labor) can often perform similar tasks across different projects and can be retained. If firms can adjust labor inputs more easily than capital inputs, we would expect that a higher capital-labor ratio weakens the effect of SPI on TFP. Our empirical findings support this prediction.

Economic theory suggests that the incentives of firms to use stock price information differ across firms depending 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 they may find it difficult to use stock price information that requires funding. We find that the impact of SPI on TFP is stronger for financially constrained firms. 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 allocate resources efficiently, so that 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 informative stock prices have a positive effect on firms' TFP. It is consistent with the findings in the literature that SPI improves corporate decisions such as investment and M&A. Second, we conduct comprehensive investigations on characteristics which amplify or minimize the effect SPI has on TFP. Relevant firm characteristics, financial frictions, product market competition, and governance all play important roles. Third, our paper adds to the discussion on the effect of financial markets on the real economy. There is a large literature on whether the stock market is a sideshow. Recently, David, Hopenhayn, and Venkateswaran (2016) find that learning from financial markets contributes little to firms' 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 efficient.

Section 2 introduces the measures of stock price informativeness. Section 3 describes the data sources and the sample. Section 4 provides our evidence on the impact of SPI on TFP. Section 5 shows the channels through which SPI impacts productivity. Section 6 investigates the cross-sectional variation in the impact of SPI on TFP. Section 7 provides evidence that SPI affects other measures of firm efficiency. Section 8 concludes.

2. Measures of stock price informativeness

We mainly use two measures of stock price informativeness, which are annual measures based on high frequency tick size trading, or stock daily trading activities. 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 stock price informativeness. 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.[2]

2.1. 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

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

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

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

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. Then the likelihood function for a trading day is:

$$\mathrm{L}(\alpha,\delta,\mu,\varepsilon_{\mathrm{b}},\varepsilon_{\mathrm{s}}|\mathrm{B}_i,\mathrm{S}_i) = (1-\alpha)\cdot \mathrm{P}(\mathrm{B}_i;\varepsilon_{\mathrm{b}})\cdot \mathrm{P}(\mathrm{S}_i;\varepsilon_{\mathrm{s}}) + \alpha\cdot\delta\cdot \mathrm{P}(\mathrm{B}_i;\varepsilon_{\mathrm{b}})\cdot \mathrm{P}(\mathrm{S}_i;\mu+\varepsilon_{\mathrm{s}})$$
$$+\alpha\cdot(1-\delta)\cdot \mathrm{P}(\mathrm{B}_i;\mu+\varepsilon_{\mathrm{b}})\cdot \mathrm{P}(\mathrm{S}_i;\varepsilon_{\mathrm{s}}) \tag{2}$$

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

$$\mathrm{V} = \prod_{i=1}^{I} \mathrm{L}(\alpha,\delta,\mu,\varepsilon_{\mathrm{b}},\varepsilon_{\mathrm{s}}|\mathrm{B}_i,\mathrm{S}_i), \tag{3}$$

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

Based on 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.

2.2. 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 a 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 that R^2 is smaller. To perform our decomposition, we use the following linear regression:

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

where *j* is for firm *j*, *i* is for industry *i*, and *t* is for day *t*, $\mathrm{r}_{j,i,t}$ is the stock return of firm *j* in industry *i* (three-digit SIC) on day *t*, $\mathrm{r}_{m,t}$ is the value weighted market return on day *t*, and $\mathrm{r}_{i,t}$ 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:

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

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.

2.3. 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 Fresard (2012) and Foucault and Fresard (2014). We apply two alternative versions of Gamma. The first version follows Llorente, Michaely, and Wang (2002) and Fresard (2012), where 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), where 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.

3. Data and sample

Our firm-level accounting data are from Compustat. We use TAQ data to calculate PIN and daily stock file of CRSP to calculate PSI and the standard deviation of stock returns. Institutional ownership and blockholder data are from Thomson Reuters 13F. Our governance measure, the E-index, is from

RiskMetrics. The competition variables we use are from the Hoberg-Phillips data library.[3] CEO characteristics are from Execucomp and BoardEx.

Our sample only includes firms with non-missing accounting data and non-missing 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 is available. In our analysis, we use the average PIN and PSI over the previous three years (we require at least one non-missing 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 total factor productivity (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 the previous methods (Olley and Pakes, 1996, and 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 R&D scaled by assets. The definitions for all variables can be found in the appendix. 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.[4]

4. Empirical evidence

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

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

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

4.1 Baseline regressions

The informational role of stock prices helps firms allocate their resources more efficiently. This implies that SPI has a positive effect on TFP. Our baseline regression specification regresses TFP on lagged average SPI and controls for firm characteristics, year fixed effects, and firm fixed effects:

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

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 3 years,[5] 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 firm-invariant omitted variables. Estimated coefficients on PIN are positive and highly significant in both models (t-statistics above 10). 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 5.6% (5.9%) 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 actually have a longer sample period, because its calculation relies on the CRSP daily stock files. Model 5 estimates Model 4 from 1975 to 2015. The coefficient of PSI is significantly positive, but its economic magnitude is lower.

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.

[5] In the unreported tests, we also use the average SPI of the previous 2 or 4 years. Our results remain strong and are not sensitive to the time window for the average.

4.2 Endogeneity tests

In Section 4.1, 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 the use of an instrumental variable (IV) for SPI, and through the use of difference-in-differences analyses using brokerage house research department closing and S&P 500 Index additions as plausibly exogenous events.

4.2.1 Instrumental variable approach

The IV approach is one of the standard methods to address endogeneity concerns. A valid instrumental variable (IV) of SPI needs to satisfy the following two conditions: i) the IV should be correlated with SPI; ii) the IV should affect TFP only through SPI. An industry-level average SPI seems to be an appropriate candidate because, within the industry, firms' SPI may have a common component. However, it is possible that a firm learns from the stock price of its close peers and hence is affected by their SPI, which would violate the exclusion restriction. To avoid this issue, we construct an IV as follows. We call the average SPI of firms in a 3-digit industry the industry-level SPI. Our IV is obtained by taking the average of the industry-level SPIs within the two-digit industry of a firm, excluding the industry-level SPI of the industry of the firm. Excluding the industry of the firm in constructing the IV alleviates the concern that the exclusion restriction might be violated. It is unlikely that a firm's TFP is affected by the SPI of an average firm in another 3-digit SIC industry code except through the correlation of that SPI with the firm's SPI. We estimate two-stage least squares (2SLS) regressions with firm and year fixed effects using that IV. The results are reported in Table 3.

Models 1 and 2 are for PIN as the measure of SPI using the previously described industry SPI as instrument. The first stage regression, where PIN is the dependent variable, is in Model 1. The coefficient of the 2-digit SIC industry average SPI is positive and statistically significant at the 1% level. The F-statistic in the first stage is 247.14, which provides strong support for the relevance condition. Model 2 reports the second-stage regression where TFP is the dependent variable. The coefficient on the instrumented PIN is positive and statistically significant at the 1% level. This result indicates that the effect of PIN on TFP remains strong. Models 3 and 4 provide estimates using PSI. They are consistent with those of Models 1 and 2. In the two-stage least squares test, PSI also has a significantly positive effect on TFP. The results of the IV method support the causal effect of SPI on TFP.

A concern with our instrumental approach is that our TFP measure could have some industry component which could drive the results of our IV tests. To address this possibility, we regress our TFP measure on industry and year indicator variables. We then use this filtered TFP measure in our IV tests. Our results (not reported) are similar.

4.2.2 DiD analysis

In this section, we carry out difference-in-differences analyses based on plausibly exogenous shocks to firms' SPI. Specifically, we first use brokerage house closures as exogenous shocks to the information production of the covered stocks (Kelly and Ljungqvist, 2012). Such events involve the closure of brokerage house research departments as well. These research departments provide information production to their clients, including both institutional and retail clients. Their research affects the generation of both private and public information on the firms they cover. Second, we consider the impact of additions to the S&P 500 Index on firm productivity through their impact on SPI.

4.2.2.a Research department closures

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. So, these shocks to the firms' stocks are largely exogenous.

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 IBES. Of the 22 closures listed, we are able to match 7 using the last date a brokerage appears in IBES and the number of firms it covers. The first closure event is in 2000 and the last is in 2007. We define the yearly event window for each closure as [-3, +3] years. It leads to a test sample from 1997 to 2010.

We define a dummy variable, $Treatment\_Post$, which equals one if a firm experienced a brokerage closure over the last one, two, or three years, and zero otherwise. The DiD specification is as follows:

$$TFP_{it} = \beta_0 + \beta_1 \cdot Treatment\_Post_{it} + X_{it} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}, \tag{7}$$

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 6.4% 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 check if the treated group and the control group have similar TFPs before the shocks, we define an indicator variable, $Treatment\_Pre$, which equals one if the firm experienced a brokerage closure in the following one, two or three years and zero otherwise. We estimate the following regression:

$$TFP_{it} = \beta_0 + \beta_1 \cdot Treatment\_Post_{it} + \beta_2 \cdot Treatment\_Pre_{it} + X_{it} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}, \tag{8}$$

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 result is reported in Model 2 of Table 4.

Model 2 shows that the coefficient of $Treatment\_Post$ is still significantly negative, consistent with the result of Model 1. However, the coefficient of $Treatment\_Pre$ is not statistically significant. This indicates that in the years before the shock, years [-3, -1], the treated firms' TFP is not statistically different from that of the control firms. This result supports the interpretation that the post-event decrease in TFP of treated firms is caused by the brokerage house closures which served as negative exogenous shocks to SPI.

We also construct a propensity score matched (PSM) sample, and carry out the DiD analysis on this PSM sample. In the PSM sample, the treated firms are those which experience brokerage closures and control firms are those that do not. We first restrict the potential control firms to those i) which have at least one analyst covering the firms, ii) are not covered by any of the seven 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. For the matched sample, we estimate the same regressions as those in Models 1 and 2 of Table 4. The results are reported in Models 3 and 4 of Table 4.

Model 3 shows that the coefficient of $Treatment\_Post$ is negative and statistically significant at the 1% level. This result is consistent with the result in Model 1 using the full sample. Compared to Model 1, the treatment effect more than doubles. The result in Model 4 is also consistent with that in Model 3: the treatment effect remains negative and highly significant. The treatment effect almost doubles compared to Model 2 for the full sample. The coefficient of $Treatment\_Pre$ is not statistically significant.

4.2.2.b S&P 500 Index additions

The firms in the S&P 500 Index are selected by a committee based on eight primary criteria.[6] The selected firms have little control on the selection process, so that much research that examines the impact of additions to the S&P 500 Index treats the event as exogenous (see, for instance, Harris and Gurel, 1986, and Shleifer, 1986).[7] 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

[6] 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

[7] An exception is Denis, McConnell, Ovtchinnikov, and Yu (2003).

implies that less firm-specific information is incorporated in the stock prices of firms in the index. As a result, if a firm is added to the index, its stock price informativeness falls. Accordingly, we expect that being added to the index reduces a firm's productivity.

To carry out the DiD analysis based on S&P 500 Index additions, we define a treatment dummy, $SP500\_Addition(t+1, t+3)$, which equals one if a firm was added to the S&P 500 Index over the last one, two, or three years and zero otherwise. The DiD specification is as follows:

$$TFP_{it} = \beta_0 + \beta_1 \cdot SP500\_Addition(t+1, t+3)_{it} + X_{it} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}, \tag{9}$$

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 5. Model 1 shows that a firm's TFP is significantly reduced after it is added into the S&P 500 Index.

To check if the treated group and the control group have similar TFPs before the shock, we define a pre-treatment dummy, $SP500\_Addition(t-1)$, which equals one if the firm was added to the S&P 500 Index in the following year and zero otherwise. We estimate the following specification:

$$TFP_{it} = \beta_0 + \beta_1 \cdot SP500\_Addition(t+1, t+3)_{it} + \beta_2 \cdot SP500\_Addition(t-1)_{it} + X_{it} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}, \tag{10}$$

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 result is reported in Model 2 of Table 5. The result shows that there is no significant TFP difference between treated and control groups before the index addition, which supports the parallel trend condition of our DiD analysis. The coefficient of the treatment dummy remains significantly positive, and is very similar to the coefficient in Model 1.

We also construct a propensity score matched (PSM) sample, and carry out the DiD analysis on this PSM sample. In the PSM sample, the treated firms are those which 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) which 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. For the matched sample, we estimate the same regressions as those in Models 1 and 2 of Table 5. The results are reported in Models 3 and 4 of Table 5. The DiD analysis based on the matched sample delivers very similar results to those in the full sample tests. Firms added in the S&P 500 Index experience a reduction in productivity, which supports our results that a decrease in SPI leads to lower firm productivity.

In this section, both the IV approach and the DiD analyses 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.

5. Channels for TFP improvement

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 sales) 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.

$$IO_{it} = \beta_0 + \beta_1 \cdot SPI_{i,t-3,t-1} + X_{it} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}, \tag{11}$$

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 3 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 6.

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 sales). 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 minimize SG&A costs to improve efficiency.

Models 5 to 6 show that SPI decreases labor costs. The coefficients of 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 of PIN (PSI) decreases wage payments by 3% (3%). These real effects on the revenues, the SG&A and labor costs identify some concrete channels through which SPI affects TFP.

6. Cross-sectional heterogeneity

We expect the ability and incentives of firms to take advantage of stock price informativeness to exhibit cross-sectional variation. 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 governance.

6.1 Firm characteristics

The effect of SPI on TFP should depend on firm characteristics. We consider five firm characteristics: firm size, firm age, acquisition activity, complexity, and capital intensity. 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:

$$TFP_{it} = \beta_0 + \boldsymbol{\beta_1} \cdot F_{it} \times SPI_{i,t-3,t-1} + \beta_2 \cdot SPI_{i,t-3,t-1} + \beta_3 \cdot F_{it} + X_{it} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}, \quad (12)$$

where *i* is the firm index, *t* is the year index, $SPI_{i,t-3,t-1}$ is the average of the previous 3 years of the measure of informativeness, *F* stands for the firm characteristic we are investigating. 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 7.

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 equation (12). 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 7 show the estimates. Both β_1's are negative and statistically significant at the 1% level. 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 that it is not a result driven by small firms. Specifically, if we exclude the bottom third of firms by asset size, we still find a relation between TFP and SPI (not tabulated).

Older firms are also at a disadvantage when it comes to utilizing 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 prices. 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, and Loderer, Stulz, and Waelchli, 2016). The results are reported in Table 6. Models 3 and 4 of Table 6 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.

Acquisitions are typically the largest discrete investment firms make. Any acquisition could potentially have a large impact on a firm's productivity. As discussed earlier, firms seem to gather much information from the market with respect to acquisitions. Therefore, we expect the productivity of firms with acquisitions to be more sensitive to SPI. We measure the acquisition activity by an acquisition indicator variable, which equals one if a firm carries out an acquisition in a given year and zero otherwise. The results are shown in Models 5 and 6. The coefficient of the interaction term, β_1, is positive and statistically significant at the 1% level in both models. Firms acquiring new assets utilize the information in their stock price to achieve a more efficient asset allocation and benefit more in terms of productivity as a result.

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 utilize 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 the diversification dummy, which equals one if a firm has more than one business segment and zero otherwise.[8] The results are reported in Table 7.

In Models 7 and 8, the coefficient of the diversification dummy, β_1, is negative and statistically significant at the 1% level. This indicates that diversified firms' productivity is less affected by their SPI, so that diversification weakens the effect of SPI on TFP. The stock prices of more diversified firms have less of a potential to guide the firms towards optimal resource allocation. This may be one reason why diversification hurts productivity.

Adjustment costs tend to be lower with labor than capital. For example, capital (e.g., machines and other equipment) generally has a specific function (in a specific business line) that is difficult to change. But the employees (labor) are more easily reallocated to other projects. As a result, a firm that has a higher capital-labor ratio may find it more difficult to adjust to new information obtained from the stock price. Therefore, we expect a high capital-labor ratio to weaken the effect of SPI on TFP.

The high capital-labor ratio dummy equals one if a firm's capital-labor ratio is in the top yearly tercile and zero otherwise. Models 9 and 10 in Table 7 show the estimates for that variable. The coefficient (β_1) of the interaction between High capital-labor ratio and the informativeness measure is significantly negative for both measures. In summary, the productivity of firms with a higher capital-labor ratio is less sensitive to the stock price informativeness.

Firms with risky businesses tend to rely less on the internal information and more on an outside signal. We measure business risk by the standard deviation of daily stock return during the previous year. As such, we expect the TFP of a riskier firm to be more sensitive to its SPI. Models 11 and 12 confirm the amplification effect of business risk. Both β_1's are positive and statistically significant at the 1% level. Riskier firms rely more on their SPI.

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

6.2 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 changes that require funding.[9] 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 five different financial constraint measures that are widely used in the literature. They are a dividend dummy (which equals one if the firm pays a dividend and zero otherwise), the Whited and Wu index (Whited and Wu, 2006), the Size and Age index from Hadlock and Pierce (2010), a dummy for S&P bond rating, and a dummy for S&P commercial paper rating (Denis and Sibikov, 2010). Our specification is as follows.

$$TFP_{it} = \beta_0 + \beta_1 \cdot FC_{it} \times SPI_{i,t-3,t-1} + \beta_2 \cdot SPI_{i,t-3,t-1} + \beta_3 \cdot FC_{it} + X_{it} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}, \tag{13}$$

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 3 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 8.

Table 8 estimates 10 models for 5 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. In eight of the ten models, the coefficient is statistically significant at the 1% level, and in the remaining two models, the coefficient is significant at the 5% level. These results provide strong and

[9] 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.

consistent evidence that financially constrained firms benefit more from the informativeness of their stock price.

6.3 Product market competition

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 therefore expect firms in more competitive markets to have greater incentives to make use of the information in their stock price. We should find that product market competition amplifies the effect of SPI on productivity.

We use three text-based network industry classification (TNIC) competition measures: product market fluidity (Hoberg, Phillips and Prabhala, 2014), product similarity, and TNIC HHI concentration (Hoberg and Phillips, 2016). These measures are from the Hoberg and Phillip data library. In our analysis, we define three dummy variables for high competition based on these three measures: High Similarity, High Fluidity, and Low HHI. 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:

$$TFP_{it} = \beta_0 + \beta_1 \cdot Competition_{it} \times SPI_{i,t-3,t-1} + \beta_2 \cdot SPI_{i,t-3,t-1} + \beta_3 \cdot Competition_{it}$$
$$+X_{it} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}, \quad (14)$$

where *i* is the firm index, *t* is the year index, $SPI_{i,t-3,t-1}$ is 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 utilize their informative stock prices to improve productivity. The results are reported in Table 9.

Models 1 and 2 use 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 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

59% (64%) compared to the effect for low competition firms. Models 3 and 4 show estimates for High Fluidity. Fluidity measures the extent to which rivals present competitive threats to the firm. Lastly, Models 5 and 6 provide estimates for the coefficients of Low HHI. These results are consistent with the results for the High Similarity variable. The estimates of β_1 in these models are significantly positive. All results in Table 9 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.

6.4 *Corporate governance*

Firms learn from the information in their stock price, and use the information to optimize resource allocation to increase productivity. When utilizing SPI to increase TFP, the amount of the information in the stock price is only part of the story as managerial action is required to take advantage of that information. If a firm has weak governance, the 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 the E-index (Bebchuk, Cohen, and Ferrell 2009), the G-index (Gompers, Ishii, and Metrick 2003), a high institutional ownership dummy (based on median in a year), and the number of blockholders (logarithm). Our regression model is as follows:

$$TFP_{it} = \beta_0 + \beta_1 \cdot Gov_{it} \times SPI_{i,t-3,t-1} + \beta_2 \cdot SPI_{i,t-3,t-1} + \beta_3 \cdot Gov_{it} + X_{it} \cdot \Gamma + \mu_i + \vartheta_t + \varepsilon_{it}, \quad (15)$$

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 E-index or G-index (weak governance), and positive for the SPI interaction with the remaining two measures. The results are reported in Table 10.

Models 1 and 2 show estimates for the E-index. A high value of the E-index indicates more entrenchment of managers and weaker governance. Model 1 (2) shows that the coefficient of the interaction between the E-index and PIN (PSI), β_1, is negative and statistically significant at the 1% level. Models 3 and 4 provide estimates for the interaction of informativeness with the G-index. The estimates are similar to those of the first two Models, which confirms that the SPI effect on TFP is stronger for firms with better governance.

Models 5 and 6 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 a High institutional ownership dummy, which equals one if the institutional ownership is above the median in a year, and zero otherwise. The coefficients of the interaction term in Models 5 and 6 are both positive and statistically significant. They indicate that the TFP of firms with better governance is more sensitive to SPI.

Our last governance measure is the number of blockholders (logarithm). A blockholder is a shareholder holding at least 5% of firm's shares outstanding. Blockholders have strong incentives to monitor firms because they are less likely to be free riders as some shareholders with smaller holdings. More blockholders suggests stronger governance. Models 7 and 8 show the relevant results. The positive interaction between the number of blockholders and the infomativeness measure is positive in both models, which confirms that firms with stronger governance have a stronger TFP-SPI sensitivity. The evidence from all four measures of corporate governance consistently shows that TFP for firms with better governance is more sensitive to SPI.

7 Alternative efficiency measures

Informative stock prices assist firms in allocating resources more efficiently. Besides TFP, we also test 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 Negative net income (NI) dummy. The results are shown in Table 11.

Models 1 and 2 provide estimates using the sales/book-value-of-assets ratio as 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 cost of goods sold (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 and PSI have positive coefficients which are significant at the 1% level. Models 9 and 10 report results for the Negative NI dummy. Both PIN and PSI have negative coefficients that are significant at the 1% level. The evidence for these alternative efficiency measures corroborates our earlier findings that SPI improves firms' efficiency.

8 Conclusions

Financial markets have a real effect on the economy. Informative stock prices help firms allocate resources more efficiently. Our paper provides evidence that the amount of information in stock prices has a positive effect on firm-level productivity. We investigate how this effect varies along different firm characteristics. We find that firm size, firm age, acquisition, complexity, and capital intensity all matter to the effect of SPI on TFP. We also find that financial constraints, product market competition, and better governance amplify the sensitivity of TFP to stock price informativeness.

We address potential endogeneity concerns using multiple methods. Our baseline specification includes firm fixed effect to get rid of any firm-invariant omitted variables and uses lagged measures of informativeness. More importantly, we also explore an IV approach and difference-in-differences 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.

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Appendix A: Variable definitions

Acquisition Dummy	a dummy variable equal to one if a firm spends money on an acquisition in a given year and zero otherwise
Average PIN (PSI)	the average of PIN (PSI) in the three-digit SIC industry excluding own firm
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 Waechli (2016)
Commercial Paper Rating	a dummy variable equal to one if a firm has commercial paper outstanding but does not have S&P short-term debt rating in or before that year, or has default debt rating in that year and zero otherwise
Debt/Assets	the sum of short term and long term debt scaled by total assets
Diversification Dummy	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 pays a dividend and zero otherwise
E-Index	the entrenchment index calculated following Bebchuk, Cohen, and Ferrell (2009)
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 of Llorente, Michaely, Saar and Wang, (2002)

High Assets	a dummy variable equal to one if a firm has above yearly median total assets and zero otherwise
High Capital-Labor Ratio	a dummy variable equal to one if a firm has a capital-labor ratio in the top annual tercile and zero otherwise where the capital-labor ratio is the ratio of net property, plant & equipment scaled by the number of employees
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, zero otherwise.
Log(Assets)	the natural logarithm of total book value of assets
Log(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(SG&A/Assets)	the natural logarithm of selling, general & administrative (SG&A) costs scaled by total assets
Log(Wages)	the natural logarithm of staff expenses
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
Median PIN (PSI)	the median PIN (PSI) in a three-digit SIC industry excluding own firm
Negative NI dummy	a dummy variable equal to one if a firm's net income is negative

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 & 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
ROA	return on assets is the ratio of the firm's operating income before depreciation divided by the lagged book value of total assets
Sales/Book Value	a firm's sales scaled by book value as calculated in Loderer, Stulz and Waechli (2016)
Sales/VAIP	a firm's sales scaled by the value of assets in place (VAIP) as calculated in Loderer, Stulz and Waechli (2016)
Size-Age Index	the size and age financial constraint index as calculated in Hadlock and Pierce (2010)
TFP	total factor productivity calculated following Levinsohn and Petrin, 2003 and improvements from 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 as calculated in Whited and Wu (2006)

Appendix B: TFP Estimation

Our main measure of productivity is the total factor productivity (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 a linear production function with capital and labor is:

$$y_{i,t} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \epsilon_{it} \tag{A1}$$

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, which relates to the productivity. A naïve estimation of TFP would be the residuals in Equation A1. However, when making the decision on inputs, firms (managers) can have some information on their productivity that econometricians do not know, which would make the input variables and the error term correlated. To address this endogeneity concern, the production function in Equation A1 is rewritten as follows.

$$y_{i,t} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \varepsilon_{it} \tag{A2}$$

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, ω_{it} is the part of the productivity known by the firm but not by the econometrician, and ε_{it} is the part of the productivity unknown to both the firm and the econometrician.

To calculate TFP, we first need to estimate the production function, i.e. the coefficients in Equation A2. Then the TFP is just the residual. Due to the endogeneity issue mentioned above, the OLS estimator is biased. In the literature, the effort to fix the endogeneity issue focuses on expressing ω_{it} as a function of some variables known by the econometrician. Specifically, first assume some corporate decision variable (observable) is determined by ω_{it} and the capital stock. Then express ω_{it} as a function of the corporate decision variable and the capital stock. For example, the decision variable in Olley and Pakes (1996) is investment, and the decision variable in Levinsohn and Petrin (2003) is materials. Then substitute the expression for ω_{it} in Equation 2, and estimate the coefficients in a two-step procedure.

Olley and Pakes (1996) and Levinsohn and Petrin (2003) both assume the decision variable is not affected by labor, which is the key to estimate the coefficient of labor in the first step of the two-step procedure. However, Ackerberg, Caves, and Frazer (2015) point out that such an assumption may not fit well with the data. If the data is inconsistent this assumption, the coefficient on labor would be estimated incorrectly because the true expression of ω_{it} would include labor. Ackerberg, Caves, and Frazer (2015) call this issue the functional dependence problem and propose a new method to estimate the production function.

In our paper, we use the methodology by Ackerberg, Caves, and Frazer (2015) to estimate the firm-level production function. This means our calculation does not suffer from the functional dependence problem. After estimating the production function, our firm-level TFP is calculated as the residual of the production function. This is the main TFP measure in our empirical analysis. In our robustness tests, we try an alternative firm-level TFP measure, which is calculated by Imrohoroglu and Tuzel (2014) and based on the methodology in Olley and Pakes (1996). Our results are robust to the alternative TFP measure.

To calculate the firm-level TFP, we use firm data from Compustat. The construction of the variables for the estimation follows İmrohoroğlu and Tüzel (2014). 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, ii) the price index for private fixed investment as a deflator for investment and capital (both from the Bureau of Economic Analysis), and iii) the national average wage index from the Social Security Administration.

Value added is Sales minus Material, deflated by GDP deflator. Sales are Revenue (*revt*) from Compustat. Material is Total expenses minus Labor expenses. Total expenses is Revenue less Operating income before depreciation and amortization (oibdp). Labor expenses is obtained by multiplying the number of employees (emp) by average wages from the Social Security Administration. Capital 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).

Denote the estimates of $(\beta_0, \beta_k, \beta_l)$ as $(\hat{\beta}_0, \hat{\beta}_k, \hat{\beta}_l)$. Our TFP measure is calculated as the residual of the regression as

$$y_{i,t} - \hat{\beta}_0 - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it}.$$

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 all firms in Compustat for which TFP and the stock price informativeness measures are variable 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	-0.23	-0.60	-0.23	0.15	0.67	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	0	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
Stock Return Volatility	0.03	0.02	0.03	0.04	0.02	55,492
Acquisition Dummy	0.41	0.00	0.00	1.00	0.49	65,228
Inst Own(HHI)	0.06	0.04	0.05	0.06	0.06	23,754
Blockholder	0.96	1	1	1	0.20	66,341
Diversification Dummy	0.42	0	0	1	0.49	49,727
Number Segments	1.82	1	1	2	1.21	49,727
SG&A/Assets	0.25	0.07	0.19	0.35	0.25	66,341
E-Index	2.88	2	3	4	1.54	26,134

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). In Panel B, we test additional SPI measures. The first measure is Gamma, a trading-based informativeness measure calculated in Equation (12) in Llorente, Michaely, Saar and Wang, (2002). We calculate this measure two ways. The first method (Columns 1 and 3) is as in Equation (3) in Fresard (2012) and controls for both firm and market returns, while the second method (Columns 2 and 4) only controls for firm returns as in the original Llorente, Michaely, Saar and Wang, (2002). The last additional stock price informativeness measure, Adjusted-PIN (APIN), is calculated using Equation (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. All columns are from 1994-2015 except for Column 5 in Panel A which is from 1975-2015. 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)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	TFP	TFP	TFP	TFP	TFP
PIN	0.352***		0.340***		
	[10.54]		[10.23]		
PSI		0.022***		0.023***	0.011***
		[6.52]		[6.86]	[3.80]
Log(Assets)	0.273***	0.278***	0.254***	0.258***	0.209***
	[35.75]	[34.74]	[33.21]	[32.28]	[34.91]
Tobin's Q	0.099***	0.100***	0.098***	0.098***	0.113***
	[20.26]	[19.94]	[20.01]	[19.70]	[24.21]
Cash/Assets			0.02	0.017	0.011
			[0.59]	[0.49]	[0.36]
Debt/Assets			-0.279***	-0.288***	-0.393***
			[-11.22]	[-11.21]	[-18.32]
R&D/Assets			-1.983***	-1.981***	-2.245***
			[-12.11]	[-12.00]	[-16.81]
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	64,876	62,086	64,670	61,882	106,696
R-squared	0.17	0.168	0.191	0.189	0.190

Panel B: Additional SPI measures (Gamma & APIN)

VARIABLES	(1) TFP	(2) TFP	(3) TFP	(4) TFP	(5) TFP	(6) TFP
Gamma(Market)	0.039**			0.034**		
	[2.33]			[2.07]		
Gamma(No Market)		0.035**			0.032**	
		[2.33]			[2.14]	
APIN			0.236***			0.230***
			[6.65]			[6.61]
Log(Assets)	0.272***	0.272***	0.285***	0.254***	0.254***	0.264***
	[32.67]	[32.66]	[33.85]	[30.73]	[30.73]	[31.00]
Tobin's Q	0.097***	0.097***	0.094***	0.095***	0.095***	0.092***
	[18.03]	[18.04]	[18.32]	[17.91]	[17.92]	[18.16]
Cash/Assets				0.004	0.004	0.015
				[0.10]	[0.10]	[0.40]
Debt/Assets				-0.311***	-0.311***	-0.320***
				[-11.10]	[-11.11]	[-11.73]
R&D/Assets				-1.995***	-1.995***	-2.108***
				[-11.05]	[-11.06]	[-11.33]
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	52,617	52,617	50,121	52,439	52,439	49,948
R-squared	0.169	0.169	0.172	0.192	0.192	0.196

Table 3: Instrumental variable (IV) method and 2SLS

This table presents 2SLS regressions using the IV method. The IV is constructed as follows. We first calculate the average SPI within each industry (3-digit SIC). We then take the average of the 3-digit SIC industry-level SPIs within the corresponding 2-digit SIC industry. When taking the average, we exclude the 3-digit SIC industry-level SPI for a firm, if the firm is in this 3-digit SIC industry. Then we use the average of this 2-digit SIC industry-level SPI over the previous three years (t-3 to t-1) as our IV. Columns 1 and 3 show the results of the first stage regression. Columns 2 and 4 show the results of the second stage regression. 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)
VARIABLES	PIN	TFP	PSI	TFP
Stage	1st	2nd	1st	2nd
PIN		2.207***		
		[8.64]		
PSI				0.059***
				[3.60]
SIC2 Mean PIN (Excl SIC3)	0.697***			
	[15.72]			
SIC2 Mean PSI (Excl SIC3)			0.674***	
			[25.32]	
Log(Assets)	-0.026***	0.305***	-0.505***	0.279***
	[-19.69]	[29.04]	[-30.29]	[23.56]
Tobin's Q	0.001*	0.096***	-0.028***	0.099***
	[1.78]	[19.48]	[-5.67]	[19.27]
Cash/Assets	-0.005	0.034	-0.165**	0.028
	[-0.91]	[0.97]	[-2.50]	[0.80]
Debt/Assets	0.004	-0.290***	0.350***	-0.304***
	[0.99]	[-10.93]	[6.56]	[-11.47]
R&D/Assets	-0.063***	-1.849***	-0.728***	-1.937***
	[-3.48]	[-11.44]	[-3.26]	[-11.86]
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
F-stat	247.14		640.86	
Observations	62,519	62,519	59,780	59,780

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 1997 to 2010. A firm is defined as a treated firm if its stock is covered by a closed research department. For each closure event, we define the event window as [-3, +3]. The dummy Treatment_Post (Treatment_Pre) equals 1 if a stock is covered by a closed research department and the year is between one and three years after (before) the closure year and 0 otherwise. Closure years are dropped in the regressions. Columns 1 and 2 use the full sample. Columns 3 and 4 use a matched sample. In the matched sample, for each treated firm, we match a control firm in the same industry (2-digit SIC) by total assets and Tobin's Q using Mahalanobis distance. 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)
VARIABLES	TFP	TFP	TFP	TFP
Sample	Full	Full	Matched	Matched
Treatment_Post	-0.043**	-0.050**	-0.106***	-0.096***
	[-2.33]	[-2.51]	[-4.10]	[-3.48]
Treatment_Pre		-0.023		0.029
		[-1.24]		[0.99]
Log(Assets)	0.273***	0.273***	0.260***	0.259***
	[28.97]	[28.98]	[9.90]	[9.82]
Tobin's Q	0.085***	0.085***	0.103***	0.102***
	[16.95]	[16.98]	[8.87]	[8.85]
Cash/Assets	0.010	0.010	0.083	0.080
	[0.24]	[0.26]	[0.73]	[0.71]
Debt/Assets	-0.311***	-0.311***	-0.130*	-0.125
	[-11.32]	[-11.35]	[-1.68]	[-1.62]
R&D/Assets	-2.129***	-2.132***	-2.063***	-2.053***
	[-11.68]	[-11.69]	[-3.83]	[-3.81]
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	44,145	44,145	4,410	4,410
R-squared	0.197	0.197	0.216	0.216

Table 5: DiD analysis: S&P 500 Index additions and productivity

This table shows DiD tests based on S&P 500 Index additions. The treatment dummy, SP500_Addition (t+1, t+3), equals 1 if a firm is added to the S&P 500 Index over the previous one, two, or three years, and 0 otherwise. The pre-treatment dummy, SP500_Addition (t-1), equals 1 if the firm is added to the S&P 500 Index in the following one year and 0 otherwise. Columns 1 and 2 use the full sample. Columns 3 and 4 use a matched sample. In the matched sample, for each treated firm, we match a control firm in the same industry (2-digit SIC) by total assets and Tobin's Q using Mahalanobis distance. 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
Sample	Full	Full	PSM	PSM
SP500 Addition(t+1, t+3)	-0.049***	-0.048***	-0.058**	-0.056**
	[-2.67]	[-2.59]	[-2.43]	[-2.36]
SP500 Addition(t-1)		0.019		0.036
		[0.92]		[1.24]
Log(Assets)	0.232***	0.232***	0.211***	0.210***
	[29.73]	[29.72]	[9.83]	[9.83]
Tobin's Q	0.095***	0.095***	0.102***	0.101***
	[15.15]	[15.16]	[6.71]	[6.63]
Cash/Assets	0.042	0.042	0.164	0.166
	[1.24]	[1.24]	[1.36]	[1.38]
Debt/Assets	-0.271***	-0.271***	-0.273***	-0.271***
	[-10.59]	[-10.58]	[-3.11]	[-3.08]
R&D/Assets	-1.856***	-1.855***	-1.270	-1.256
	[-10.29]	[-10.29]	[-1.59]	[-1.57]
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	41,242	41,242	3,940	3,940
R-squared	0.229	0.229	0.200	0.200

Table 6: Channels for TFP improvement

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 sales), and the labor cost is measures by the labor 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. 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)
VARIABLES	Log(Revenue)	Log(Revenue)	SG&A	SG&A	Log(LaborCost)	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***	-0.180	-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]		
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
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

Table 7: 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. 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)	(9)	(10)	(11)	(12)
Firm Characteristic	High Assets		Firm age		Acquisition		Diversification		Capital-labor ratio		Business Risk	
Firm Characteristic x PIN	-0.234***		-0.016***		7.654***		-0.189***		-0.153***		7.805***	
	[-4.13]		[-6.60]		[4.88]		[-3.33]		[-2.60]		[4.94]	
Firm Characteristic x PSI		-0.020***		-0.001***		1.134***		-0.012***		-0.011**		1.145***
		[-4.18]		[-7.48]		[9.72]		[-2.96]		[-2.48]		[9.80]
PIN	0.419***		0.571***		0.137**		0.407***		0.392***		0.134**	
	[10.09]		[10.81]		[2.39]		[9.31]		[9.75]		[2.32]	
PSI		0.028***		0.045***		-0.013***		0.030***		0.026***		-0.014***
		[7.92]		[10.01]		[-2.68]		[7.40]		[7.03]		[-2.77]
Firm Characteristic	0.258***	0.263***	-0.007***	-0.007***	-4.418***	-5.749***	0.001	-0.012	-0.107***	-0.112***	-4.436***	-5.771***
	[32.14]	[31.27]	[-5.41]	[-5.84]	[-8.94]	[-12.55]	[0.05]	[-0.89]	[-6.24]	[-6.97]	[-8.90]	[-12.56]
Other Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
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
Observations	64,670	61,882	63,414	60,653	54,183	51,917	49,412	47,517	64,670	61,882	53,360	51,097
R-squared	0.192	0.19	0.196	0.195	0.2	0.2	0.2	0.198	0.197	0.195	0.200	0.201

Table 8: 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 five financial constraint measures: dividend dummy, Whited-Wu index, Hadlock and Pierce (2010) size and age index, bond rating dummy and commercial paper rating dummy. 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. 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)	(9)	(10)
Fin Constraint	Dividend		Whited-Wu		Size & Age		Bond Rating		Comm'l Paper Rating	
PIN x Fin Const.	0.185***		0.816***		0.141***		0.216***		0.514***	
	[3.50]		[2.92]		[3.00]		[3.57]		[7.55]	
PSI x Fin Const.		0.017***		0.052**		0.010**		0.013***		0.040***
		[4.26]		[2.11]		[2.43]		[2.59]		[5.97]
PIN	0.233***		0.547***		0.822***		0.195***		-0.121**	
	[5.71]		[5.72]		[4.71]		[4.27]		[-2.10]	
PSI		0.013***		0.035***		0.063***		0.013***		-0.016**
		[3.19]		[4.51]		[4.08]		[2.69]		[-2.27]
Fin Const.	-0.066***	-0.061***	0.679***	0.822***	-0.001	0.010	-0.039*	-0.023	-0.076***	-0.038*
	[-4.34]	[-4.64]	[5.36]	[6.41]	[-0.04]	[0.25]	[-1.92]	[-1.16]	[-3.26]	[-1.75]
Other Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	64,471	61,690	63,444	60,686	58,345	55,897	56,977	54,495	56,492	54,040
R-squared	0.192	0.190	0.198	0.197	0.195	0.194	0.183	0.180	0.184	0.182

Table 9: 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, 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. 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	High Similarity		High Fluidity		Low HHI	
Competition x PIN	0.247***		0.151**		0.188***	
	[4.00]		[2.53]		[4.13]	
Competition x PSI		0.018***		0.010**		0.013***
		[4.05]		[2.53]		[4.02]
PIN	0.419***		0.137**		0.298***	
	[10.09]		[2.39]		[7.82]	
PSI		0.028***		-0.013***		0.021***
		[7.92]		[-2.68]		[5.76]
Competition	0.258***	0.263***	-4.418***	-5.749***	-0.039***	-0.043***
	[32.14]	[31.27]	[-8.94]	[-12.55]	[-3.50]	[-5.57]
Other Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	49,417	47,265	45,857	43,850	49,417	47,265
R-squared	0.382	0.378	0.390	0.388	0.381	0.378

Table 10: Corporate governance and the complementary effect

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 the E-index (Bebchuk, Cohen, and Ferrell, 2009), the G-index (Gompers, Ishii, and Metrick, 2003), a high institutional ownership dummy (based on median in a year), and the number of blockholders (logarithm). 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. 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)
Governance Measure	E-Index		G-Index		High Inst Ownership		Log(N_Blockholders)	
Governance x PIN	-0.077***		-0.075***		0.170**		0.151**	
	[-2.92]		[-4.73]		[2.07]		[2.05]	
Governance x PSI		-0.006**		-0.003*		0.024***		0.018***
		[-2.42]		[-1.90]		[4.09]		[3.45]
PIN	0.405***		0.867***		0.199***		0.116	
	[4.85]		[5.39]		[2.79]		[1.24]	
PSI		0.028***		0.040**		0.010		0.000
		[3.14]		[2.14]		[1.42]		[0.01]
Governance	-0.001	-0.007	0.003	-0.007	-0.002	-0.001	-0.066***	-0.062***
	[-0.13]	[-1.13]	[0.43]	[-0.95]	[-0.10]	[-0.07]	[-4.62]	[-6.19]
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
Observations	24,958	23,857	15,710	15,175	22,799	21,717	22,799	21,717
R-squared	0.215	0.212	0.201	0.199	0.222	0.219	0.224	0.220

Table 11: 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 are from Loderer, Stulz and Waechli (2016). 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. 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)	(9)	(10)
VARIABLES	Sales/Book Value	Sales/Book Value	Sales/VAIP	Sales/VAIP	COGS/Emp	COGS/Emp	ROA	ROA	Negative NI	Negative NI
PIN	0.043**		0.203*		4.738		0.055***		-0.581***	
	[2.07]		[1.90]		[0.67]		[5.77]		[-2.97]	
PSI		0.012***		0.074***		-1.769***		0.009***		-0.136***
		[5.55]		[4.27]		[-2.62]		[9.26]		[-7.62]
Log(Assets)	-0.550***	-0.532***	-0.971***	-0.866***	55.509***	54.090***	0.022***	0.028***	-0.477***	-0.538***
	[-50.59]	[-49.39]	[-26.58]	[-15.42]	[21.19]	[19.94]	[6.74]	[10.76]	[-15.91]	[-16.78]
Tobin's Q	0.013***	0.014***	-0.007	-0.029***	2.887***	2.837***	0.011*	0.018***	-0.686***	-0.676***
	[7.62]	[7.93]	[-1.07]	[-2.77]	[7.13]	[6.99]	[1.73]	[15.26]	[-28.46]	[-27.80]
Cash/Assets	-0.397***	-0.397***	-1.135***	-1.286***	-19.307***	-20.782***	0.079***	0.071***	-1.734***	-1.743***
	[-19.65]	[-19.83]	[-12.47]	[-9.16]	[-3.32]	[-3.49]	[5.33]	[6.89]	[-11.01]	[-10.86]
Debt/Assets	-0.067***	-0.064***	1.245***	0.433**	-18.142***	-17.451***	-0.243***	-0.249***	4.054***	4.089***
	[-3.64]	[-3.54]	[9.21]	[2.12]	[-4.01]	[-3.76]	[-12.25]	[-11.90]	[34.04]	[33.32]
R&D/Assets	0.652***	0.691***	1.209***	0.898	58.200***	55.236***	-0.793***	-0.796***	15.034***	14.831***
	[8.37]	[8.82]	[2.72]	[1.19]	[2.78]	[2.63]	[-14.62]	[-14.90]	[23.12]	[22.69]
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]				
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	63,739	60,955	63,739	60,955	63,740	60,956	63,740	60,956	43,480	41,413
R-squared	0.470	0.466	0.108	0.034	0.288	0.284	0.102	0.152	0.152	0.154