Firm-specific investor sentiment and productivity

Haifeng Guo[1], Wenyi Sun[2], and Yeqin Zeng*[1]

[1] *Durham University Business School, Durham University, Durham, DH1 3LB, UK*
[2] *Surrey Business School, University of Surrey, Surrey, GU2 7XH, UK*

Abstract

This paper examines the impact of firm-specific investor sentiment (FSIS) on firm productivity. Using a sample of U.S. public firms from 2010 to 2019, we document a positive relation between FSIS and total factor productivity (TFP). The positive relation remains robust to a difference-in-differences analysis based on firms' additions to the S&P 500 index or the Russell 1000 index, high-dimensional fixed effects, and FSIS measured by its change or lagged term. We also find that the positive impact of FSIS on productivity is more pronounced for firms with less exposure to automated production, more managerial ownership, tighter financial constraints, and higher innovative efficiency. Moreover, we show that FSIS is positively related to firms' operational efficiency and profitability. Taken together, our findings generate an important insight that investment sentiment, a phenomenon in the financial market that biases expected firm performance, has a real impact on corporate production efficiency.

Keywords: Firm-specific investor sentiment; Total factor productivity; Overnight returns; Order imbalance; Earnings conference call sentiment

*Corresponding author: Associate Professor, Durham University Business School, Mill Hill Lane, Durham, DH1 3LB, United Kingdom. Tel. +44(0)1913345095. E-mail addresses: yeqin.zeng@durham.ac.uk (Y. Zeng), e.sun@surrey.ac.uk (W. Sun), haifeng.guo@durham.ac.uk (H. Guo).

1. Introduction

Productivity, the efficiency of firms converting inputs into outputs, has attracted great attention in previous economics and finance studies. With an increase in productivity, firms produce more outputs with a fixed set of inputs. Syverson (2004) finds that based on the productivity distribution within four-digit SIC industries in the U.S. manufacturing sector, the 90th percentile firms' total factor productivity (TFP) is nearly twice as much as the TFP of the 10th percentile firms. Syverson (2011) and Heil (2018) summarize the determinants of firm productivity in the literature, which provide rational explanations for the large and persistent differences in productivity. For example, firm productivity increases with information technologies (Bloom et al. 2012), access to external finance (Krishnan et al. 2015), and stock price informativeness (Bennett et al. 2020). However, it remains unknown whether behavioral finance helps to explain the cross-sectional difference in firm productivity once we assume the existence of sentiment-driven investors in the financial market.

The behavioral finance literature defines investor sentiment as optimism or pessimism about firms' future cash flows that are not justified by publicly available fundamental information (e.g, Lamont & Stein 2004, Baker & Wurgler 2006, Stambaugh et al. 2012). A recent strand of empirical study has shown that corporate decision-making activities are responsive to the presence of sentiment-driven investors, such as capital investment, mergers and acquisitions, stock splits, initial public offerings (IPOs), and external financing (e.g., Baker et al. 2003, Gilchrist et al. 2005, Dong et al. 2006, Polk & Sapienza 2008, Baker et al. 2009, Dorn 2009, Alimov & Mikkelson 2012, Dong et al. 2012, Arif & Lee 2014, McLean & Zhao 2014). Nevertheless, the literature has remained largely silent about the role of investor sentiment on corporate outcomes regarding productivity. Since firm productivity is an essential component of all economic activities, it is important to understand whether sentiment in the financial market may affect firm productivity, and how investor sentiment shapes production efficiency and propagates to the real economy. In this study, we attempt to fill the gap in the literature by assessing the empirical relation between firm-specific investor sentiment (FSIS) and productivity.

A major challenge in the sentiment literature is to identify and quantify investor sentiment. Most of the previous studies extract investor sentiment information from surveys of consumer and investor confidence (e.g. Brown & Cliff 2005, Lemmon & Portniaguina 2006) or adopt indirect sentiment measures based on a list of market variables (e.g. Baker & Wurgler 2006, 2007). Based on these aggregated sentiment proxies, researchers examine how market-level sentiment affects firm-level policies and disclosures (e.g., Bergman & Roychowdhury 2008, Hribar & McInnis 2012, Mian & Sankaraguruswamy 2012, Walther & Willis 2013, Li & Luo 2017, Dang & Xu 2018). However, market-level sentiment proxies may not provide a full picture of how sentiment in the financial market influences firm-level issues, given that high and low individual firm sentiment can be neutralized. Furthermore, when sentiment is aggregated market-wide, it only varies over time but does not have any cross-sectional variations (Aboody et al. 2018). Therefore, FSIS may better serve the purpose of explaining the cross-sectional differences in firm productivity than market-level sentiment measures.

To better identify and understand the direct effect of investor sentiment on productivity at the firm level, we employ three measures of FSIS: stock overnight (close-to-open) returns proposed by Aboody et al. (2018), retail investor order imbalance developed by Boehmer et al. (2021), and non-political sentiment derived from the transcripts of earnings conference calls by Hassan et al. (2019). To measure firm productivity, we adopt total factor productivity estimated by İmrohoroğlu & Tüzel (2014) as our main proxy for firm productivity, and two alternative measures of productivity proposed by Ackerberg et al. (2015) and Jacob (2021) in our robustness tests. Using a sample of U.S. public firms from the CRSP/Compustat Merged database between 2010 and 2019, our baseline regression indicates a significantly positive relation between FSIS and TFP. A one-standard-deviation increase in FSIS is associated with a 1.6% to 7.1% increase in TFP, depending on the FSIS proxy. Our result strongly supports the view that a firm is more productive when investors in the financial market are optimistic about the firm's future performance and growth opportunities.

To assert the causal interpretation of our main finding, we adopt three tests to address the potential endogeneity due to omitted variable bias and reverse causality. First, we take advantage of quasi-natural experiments based on stocks' additions to the S&P 500 index and the Russell 1000 index, and conduct difference-in-differences (DID) tests. Since firms added to the two indices have no control over the process of selecting index constituents, previous literature usually considers the addition events as exogenous shocks (e.g., Harris & Gurel 1986, Chang et al. 2015). It is unlikely that the index additions directly affect firm productivity without a intermediary variable. We verify that FSIS increases after firms' stocks are added to the corresponding indices. After matching the treated firms that are added to the two indices with the control firms that are not in the corresponding indices, we show that the treated and control firms do not have significant differences in their TFP three years before the addition events. However, we find that the TFP of the treated firms is significantly higher than the TFP of the control firms up to three years after the addition events. Second, we follow Gormley & Matsa (2014) and mitigate the estimation bias due to time-invariant and firm-specific omitted variables by controlling for the firm fixed effects and the Fama-French 48 industry × year fixed effects in our baseline regression. Third, we alleviate simultaneity and reverse causality concerns by replacing the level of FSIS in our baseline regression with the change in FSIS over a year or one-year lagged FSIS. Our main finding remains robust to all three identification tests.

We next investigate the mechanisms through which FSIS influences TFP by cross-sectional analyses. First, we find that the positive effect of FSIS on TFP is more pronounced for firms with lower exposure to automation technology. Since a production process utilizing automation technology is unlikely to be affected by human emotion or sentiment, our finding indicates a sentiment spillover channel that investors' optimistic view on firms spilsl over to their employees and managers, and subsequently incentivizes them to enhance the productivity of the production process with human intervention. Second, we show that the positive relation between FSIS and TFP is stronger among firms with higher managerial ownership. This evidence complements the catering channel identified by Polk & Sapienza (2008) and Dong et al. (2012), in which managers are more likely to invest when the market is optimistic about their firms. In the same vein, we find that managers with higher firm ownership improve firm productivity for the purpose of catering to current investor sentiment. Third, we find a greater impact of FSIS on TFP for firms with financial constraints than those without. This finding is in line with the view that firms have better access to external financing when market sentiment is higher (e.g., McLean & Zhao 2014, Dang & Xu 2018) and the notion that productivity increases with firms' external borrowing ability (e.g., Butler & Cornaggia 2011, Krishnan et al. 2015). At last, we find that the positive effect of FSIS on TFP is more prominent for firms with higher innovation efficiency, suggesting that high FSIS helps to foster firms' innovation which in turn improves productivity for those with a higher innovation ability.

In our supplementary tests, we first assess whether our results are influenced by potential bias of our productivity estimation. The results show that our finding is unaffected when we replace İmrohoroğlu & Tüzel's (2014) TFP with alternative TFP measures. We then test the persistence of the impact of FSIS on TFP and find that FSIS has a positive impact on TFP in the following three years but the impact shrinks over time. We also extend our sample period to 1992–2019 and 2002–2019 during which we have available data to construct FSIS proxies based on overnight returns and earnings conference call transcripts. The positive relation between FSIS and TFP remains robust. Lastly, we find that a firm's operational efficiency and profitability also increase with FSIS, while the likelihood of operating income loss is negatively related to FSIS.

Our paper contributes to the literature in several ways. First, to the best of our knowledge, we are the first to document that investor sentiment at the firm level can exert a real economic impact on firm productivity. Existing literature in behavioral finance mainly focuses on the role of market-level investor sentiment in asset pricing (see., Baker & Wurgler 2006, 2007, Barber et al. 2009, Yu & Yuan 2011, Baker et al. 2012, Stambaugh et al. 2012, Da et al. 2015, Huang et al. 2015, Yuan 2015) and corporate finance (e.g., Gilchrist et al. 2005, Polk & Sapienza 2008, Baker et al. 2009, Dorn 2009, Alimov & Mikkelson 2012, Dong et al. 2012, Arif & Lee 2014, McLean & Zhao 2014, Dang & Xu 2018). However, the literature pays far less attention to the impact of FSIS on real outcomes, such as productivity, that are fundamental for economic growth. Our paper extends this strand of literature by exploring the direct linkage between FSIS and firm productivity.

Second, prior literature mainly focuses on using market-level investor sentiment to examine firm-level activities and try to draw a causal relation, whereas we explore a new strand by focusing on investor sentiment at the firm level. Since market-level sentiment only reflects the time-series variations while FSIS exhibits both time-series and cross-sectional variations, FSIS has more power than market-level sentiment to explain the cross-sectional differences in corporate activities (Aboody et al. 2018). Kim & Kim (2014) argue that investors' excessive optimism and excessive pessimism about different firms can be canceled out at the market level, therefore relying on FSIS measures minimizes the likelihood of drawing biased inferences on the empirical relation between sentiment and corporate activities. In addition, confounding macroeconomic factors, such as business cycles and monetary policy, may be associated with both market-level sentiment and corporate activities (Sibley et al. 2016). Our paper adopts three FSIS measures proposed by most recent sentiment studies (Aboody et al. 2018, Hassan et al. 2019, Boehmer et al. 2021), which helps to avoid the concern of a spurious relation between FSIS and TFP driven by unobserved macroeconomic variables.

Third, this paper adds to the literature on the determinants of firm productivity. We show that besides well-documented external drivers of productivity (e.g., Syverson 2011, Heil 2018), the sentiment of investors in the financial market plays an important role in explaining a firm's production efficiency. The implication of investor sentiment for productivity yields valuable insights into the behavioral nature of how firms turn inputs into outputs. We also uncover evidence that the impact of FSIS on firm productivity is through the mechanisms of sentiment spillover, managers catering, external financing, and innovation efficiency. It is not clear in the literature what role behavioral investors play in influencing production activities. Our paper helps to fill this gap by providing evidence of a positive relation between FSIS and TFP and offering a new perspective on the behavioral role of the financial market in corporate policy and outcomes.

The remainder of the paper is organized as follows. Section 2 presents a brief literature review. Section 3 describes the sample, variables, and research design. Section 4 presents the summary statistics and main empirical results and explores the plausible mechanisms through which FSIS affects TFP. Section 5 provides supplementary test results. Section 6 concludes.

2. Prior literature and prediction

2.1. Firm productivity

Firm productivity refers to a firm's efficiency in transforming its capital inputs and labor inputs into outputs. Early literature has devoted much attention to address the potential endogeneity in the estimation of production functions (e.g., Marschak & Andrews 1944, Hoch 1955, Mundlak & Hoch 1965, Christensen et al. 1973, McElroy 1987), whereas the estimation methods proposed by Olley & Pakes (1996), Levinsohn & Petrin (2003), Ackerberg et al. (2015) have been widely used in empirical studies. For example, İmrohoroğlu & Tüzel (2014) use Olley & Pakes's (1996) method and estimate the firm-level TFP for U.S. public firms. They find that TFP is positively related to contemporaneous monthly stock returns but negatively associated with future excess returns. In addition, they show that firms with lower TFP tend to be firms with smaller size, less investment, lower hiring rates, larger book-to-market ratios, and higher firm risk.

Previous economics studies also investigate what determines a firm's productivity. Syverson (2011) summarizes four main drivers of firm productivity documented in the economics literature: productivity spillovers among producers, intra- and inter-market competition, change in regulation, and input market flexibility and efficiency. Heil (2018) reviews the empirical work on the relation between business finance and productivity and indicates that financial development fosters productivity growth, while financial frictions hamper productivity growth. Heil (2018) also highlights the channels through which finance influences productivity: human capital, corporate finance, financial market efficiency, and financing through public and private equity markets.

A recent strand of finance study investigates how stock price informativeness, external financing, and corporate investment affect TFP. Bennett et al. (2020) find that when managers can learn more firm-specific information from their firms' stock prices, they allocate internal resources more efficiently, leading to higher firm productivity. Levine & Warusawitharana's (2021) theoretical model demonstrates that financial frictions increase the sensitivity of productivity growth to the use of external borrowing. Krishnan et al. (2015) provide empirical evidence that firms' TFP increases after their access to bank financing is enhanced due to the deregulation of local state banking systems. Moran & Queralto (2018) develop a model to identify the dynamic effect of innovation on productivity and prove that an increase in aggregate private R&D investment induces a gradual and persistent increase in firm productivity. Consistent with Moran & Queralto's (2018) model prediction, Balasubramanian & Sivadasan (2011) and Jacob (2021) show that new patent grants and capital investment are positively related to firm productivity.

2.2. Investor sentiment

The classical finance theory, in which rational arbitrageurs always drive asset prices to the present value of expected cash flows associated with the assets, leaves no role for investor sentiment. Keynes (1936) argues that investor behaviors may decouple asset prices from their associated fundamental values, due to the well-known psychological fact that investors with high (low) sentiment are more likely to make overly optimistic (pessimistic) judgments. Over time, researchers in behavioral finance formalize the role of investor sentiment in financial markets. De Long et al. (1990) show that investors are subject to sentiment and the change in investor sentiment leads to more noise trading, greater asset mispricing, and excess market volatility. There is also a growing consensus in the literature that investor sentiment helps explain stock returns (Kothari & Shanken 1997, Neal & Wheatley 1998, Nicholas et al. 1998, Baker & Wurgler 2000, Brown & Cliff 2005). More recent finance studies examine the relationship between investor sentiment and corporate decisions, such as capital investment, dividend policy, equity issuance, and innovation (Baker & Wurgler 2007, Stambaugh et al. 2012, Alimov & Mikkelson 2012, Dong et al. 2012, Arif & Lee 2014, McLean & Zhao 2014, Dang & Xu 2018). The accounting literature also shows that the disclosure of financial information is responsive to investor sentiment (Hribar & McInnis 2012, Mian & Sankaraguruswamy 2012, Walther & Willis 2013, Livnat & Petrovits 2019). For example, during low-sentiment periods, managers increase long-horizon earnings forecasts to maintain current investor optimism (Bergman & Roychowdhury 2008), while during high-sentiment periods, managers are more likely to disclose earnings numbers higher than those based on the generally accepted accounting principles (GAAP) (Brown et al. 2012).

However, most of these empirical studies rely on market-level sentiment proxies, such as Baker & Wurgler's (2006) sentiment index and the University of Michigan consumer sentiment index. Aboody et al. (2018) argue that market-level sentiment varies over time but does not have cross-sectional variations invariant, which may not be well suited to address firm-level issues. As such, a few studies focus on firm-level measures of investor sentiment by observing retail investor behavior and by extracting sentiment from news media. For instance, Cornelli et al. (2006) use pre-IPO prices of 486 European companies to proxy for retail investors' sentiment, and Kumar & Lee (2006) measure FSIS using the buy-sell order imbalance of retail investors. Tetlock (2007) extracts investor sentiment from the Wall Street Journal and Danbolt et al. (2015) proxy FSIS based on Facebook status updates. Our paper is closely related to Aboody et al. (2018), Hassan et al. (2019), and Boehmer et al. (2021), who develop firm-level sentiment measures which enable us to proxy for investor sentiment at the firm level.

2.3. Empirical prediction

The research into the productivity differences across firms in the same industry has identified both firm- and market-level factors shaping the productivity distribution. No study has directly investigated the link between investor sentiment and firm productivity, especially for sentiment measured at the firm level. This is important given the recent strand of literature showing that investor sentiment plays an important role in explaining stock returns and corporate decisions. The availability of data on FSIS also offers us an opportunity to examine the empirical relation between sentiment and productivity at the micro-level. As previously shown in the literature on investor sentiment, a firm's decision on whether to react to investor sentiment is based on a trade-off between maximizing the long-term fundamental value by taking activities to increase the present value of future cash flows and maximizing the current stock price by engaging in activities that cater for sentiment-driven investors (Baker & Wurgler 2013). Meanwhile, both managers' decisions to improve the efficiency of resource allocation and production process and employees' motivation to increase labor productivity depend on their wealth and compensation tied to their firms' stock prices. As an outcome of a firm's decision, our measure of firm productivity, TFP, reflects the difference between actual outputs and expected outputs, where expected outputs are computed using fixed capital and labor inputs in the production process. If investor sentiment facilitates an upsurge in TFP, which in turn feeds back into stock price, managers and employees' wealth will ultimately increase. Taken together, we predict that FSIS has a positive impact on TFP along the following four dimensions.

First, it is well documented in the psychology literature that positive attitude and mood lead to enhanced cognitive flexibility and performance (e.g., Mirvis & Lawler 1977, Ostroff 1992, Nadler et al. 2010, Tenney et al. 2016). If investor sentiment in the financial market has a spillover effect on the morale of managers and employees, then higher FSIS will motivate managers to make better decisions to allocate resources and stimulate employees' work performance, resulting in higher firm productivity. Consistent with this notion, Dang & Xu (2018) show that high market sentiment leads to high manager sentiment, which in turn encourages firms to engage in more innovation activities. Second, since managers have a propensity to cater for investors' preference for corporate policies (e.g., Baker & Wurgler 2004*b*,*a*), the managers of firms with high investor sentiment are likely to undertake more productive projects that cater for investors' high expectation on future firm growth, which leads to an increase in firm productivity. Polk & Sapienza (2008) show that if the market overestimates a firm's value based on its investment, the firm's managers may cater for market sentiment and boost the short-term firm stock price by increasing investment. Third, prior research indicates that when investors are more optimistic about a firm's future cash flows, the firm may benefit from getting better access to external financing (e.g. Dong et al. 2012, McLean & Zhao 2014). Butler & Cornaggia (2011) and Krishnan et al. (2015) provide evidence that an increase in firms' external borrowing ability positively influences their productivity and the impact is more pronounced for firms with financial constraints. These findings suggest that high FSIS facilitates firms' access to external financing and subsequently improves firm productivity. Finally, Dang & Xu (2018) show that firms invest more in R&D when market sentiment is high. Since productivity is positively associated with firms' innovative outputs (Kogan et al. 2017), we predict that the technology developments derived from sentiment-driven innovative projects enhance firm productivity.

3. Sample, variables, and research design

3.1. Data sources and sample

Our sample consists of all U.S. firms listed in the New York Stock Exchanges (NYSE), American Stock Exchange (AMEX), and NASDAQ from the Center for Research in Security Prices (CRSP). Our sample period starts in 2010, the earliest year with data available for one of our three FSIS measures, and ends in 2019, the latest year with complete data on our main measure of TFP. Following İmrohoroğlu & Tüzel (2014), we exclude firms in financial and utility industries (SIC codes 6000–6999 and 4900–4999, respectively). We retrieve firm accounting data from the Compustat database, data on daily stock prices and S&P 500 index constituents from the CRSP database, data on Russell 1000 index constituents from the FTSE/Russell database, and stock transaction data from the Trade and Quote (TAQ) database. We also collect the firm-level TFP data from Şelale Tüzel's website, sentiment data based on the tone of earnings conference call transcripts from Tarek A. Hassan's website, market-level investor sentiment index data from Jeffrey Wurgler's website, data on the Consumer Price Index (CPI) from the Federal Reserve Bank of St. Louis' website, data on the price index for Gross Domestic Product (GDP) and the price index for private fixed investment from the Bureau of Economic Analysis' website, automation patent data from Lukas Püttmann's website, and corporate patent data from the United States Patent and Trademark Office's website. All accounting data in dollars are inflation-adjusted to 2019 dollars using the CPI. Our final sample includes 18,107 firm–year observations with 3,332 unique firms.

3.2. Measures of firm productivity

Following the literature on firm productivity (e.g., Kogan et al. 2017, Jacob 2021), we adopt İmrohoroğlu & Tüzel's (2014) TFP as our main measure of firm-level productivity. *TFP* is constructed from the following production function:

$$y_{i,t} = \beta_0 + \beta_k k_{i,t} + \beta_l l_{i,t} + \omega_{i,t} + \varepsilon_{i,t} \tag{1}$$

where i is firm index, t is year index, $y_{i,t}$ is the natural logarithm of output, $k_{i,t}$ is the natural logarithm of capital, $l_{i,t}$ is the natural logarithm of labor, $\omega_{i,t}$ is *TFP* observed by firm i before making its factor input decisions, and $\varepsilon_{i,t}$ is the residual term which is not known by firm i or econometricians. The detailed definitions of $y_{i,t}$, $k_{i,t}$, and $l_{i,t}$ are described in Appendix A. Equation (1) is based on the logarithm form of the Cobb-Douglas production function. İmrohoroğlu & Tüzel (2014) adopt Olley & Pakes's (1996) semi-parametric methodology to estimate $\widehat{\beta}_0$, $\widehat{\beta}_k$, and $\widehat{\beta}_l$, which helps to mitigate selection and simultaneity biases and to control for productivity's within-firm serial correlation.[1] The

[1] İmrohoroğlu & Tüzel (2014) also include industry-specific time dummies to the estimation, which attenuates the effect of industry or aggregate TFP in any given year. Please refer to the online appendix of İmrohoroğlu & Tüzel (2014) for the estimation procedure.

firm-level TFP, $\omega_{i,t}$, can be calculated from the three estimated parameters:

$$\omega_{i,t} = y_{i,t} - \widehat{\beta}_0 - \widehat{\beta}_k k_{i,t} - \widehat{\beta}_l l_{i,t} \tag{2}$$

As such, TFP captures the overall efficiency and effectiveness of how factor inputs are used in a firm's production process.

In our supplementary tests, we calculate two alternative measures of firm productivity and show that our main results are not driven by a specific method of estimating the production function. Our first alternative measure of TFP, *TFP_Alt1*, is also based on the Cobb-Douglas production function but is estimated by Ackerberg et al.'s (2015) method. Ackerberg et al. (2015) propose an estimator which inverts input demand functions that are conditional on the choice of labor input, while Olley & Pakes's (1996) estimation is based on inverted unconditional input demand functions. Our second alternative measure of *TFP*, *TFP_Alt2*, follows Jacob (2021) which regresses firm output (defined as earnings before tax plus depreciation and total wages) on labor (total wages) and capital (fixed assets) for each industry–year using the ordinary least squares (OLS) method. *TFP_Alt2* is the residuals of these regressions. The detailed descriptions of the two alternative measures of TFP are provided in Appendix B.

3.3. Measures of firm-specific investor sentiment

For our empirical tests, we adopt three measures of FSIS, which are based on overnight stock returns, retail investor order imbalance, and the tone of earnings conference call transcripts.

3.3.1. Overnight returns

Our first measure of FSIS is based on stock overnight returns. Previous studies document strong evidence that retail investors are most likely to be sentiment-driven (e.g., Lee et al. 1991, Barber et al. 2009, Berkman et al. 2012). Specifically, Berkman et al. (2012) find that retail investors tend to place orders outside of normal exchange trading hours which will be executed at the start of the next trading day. Berkman et al.'s (2012) finding suggests that a stock's overnight (close-to-open) return is affected by retail investors' orders and is a suitable measure of FSIS. The recent work of Aboody et al. (2018) also shows that overnight returns possess four characteristics of a sentiment measure: time-series persistence, stronger persistence of overnight returns for harder-to-value firms, stronger persistence of overnight returns for firms with lower institutional ownership, and a negative relation between overnight returns and stock long-term performance.

Following Aboody et al. (2018), we require that end-of-prior-year stock prices are greater than \$5 per share and stock market capitalization is more than \$10 million. Stock i's overnight return on day j is defined as:

$$OR_{i,j} = \frac{Open_{i,j} - Close_{i,j-1}}{Close_{i,j-1}} \tag{3}$$

where $Open_{i,j}$ is the opening price of stock i on day j and $Close_{i,j-1}$ is the closing price of stock i on day $j-1$. Both opening prices and closing prices are adjusted for stock split, stock dividends, and cash dividends. $OR_{i,j}$ is treated as missing if either $Open_{i,j}$ or $Close_{i,j-1}$ is missing in the CRSP database. We further annualize the overnight returns as $FSIS\_OR_{i,j}$ using the following equation:

$$FSIS\_OR_{i,t} = 250 \times \frac{\sum_{j=1}^{N} OR_{i,j}}{N} \tag{4}$$

where 250 is the approximate number of trading days within a fiscal year and N is the number of non-missing $OR_{i,j}$ in year t. $FSIS\_OR_{i,j}$ is treated as missing if N is less than 100.

3.3.2. Retail investor order imbalance

The second FSIS measure is based on retail investor order imbalance. Kumar & Lee (2006) find that retail investor sentiment, measured by the buy-sell order imbalance of retail investors, has a strong ability to explain the return co-movements of stocks with a high concentration of retail investor ownership and high arbitrage costs. Barber et al. (2009) further confirm Kumar & Lee's (2006) findings that collective annual small trade order imbalance predicts future stock returns, and stocks heavily bought by retail investors underperform those heavily sold by retail investors by 4.4% in the following year. In other words, stocks with high retail investor demand earn relatively low future returns, consistent with the empirical evidence of investor sentiment measures (e.g., Baker & Wurgler

2006, 2007, Stambaugh et al. 2012). A recent study by Boehmer et al. (2021) further provides empirical evidence that retail order imbalance is significantly and positively related to contemporaneous firm-level public news, suggesting that retail investor order imbalance captures the characteristics of investor sentiment.

Following Boehmer et al. (2021), we focus on trades that occur off-exchange. We first identify trades initiated by retail investors using the exchange code "D" in the TAQ database.[2] We only keep common stocks with share code 10 or 11 listed on NYSE, AMEX, and NASDAQ, and require that stock prices are above \$1 at the previous month-end. We then calculate the daily retail order imbalance of stock i on day j, $OIB_{i,j}$ as follows:

$$OIB_{i,j} = \frac{Buy_{i,j} - Sell_{i,j}}{Buy_{i,j} + Sell_{i,j}} \tag{5}$$

where $Buy_{i,j}$ ($Sell_{i,j}$) is the aggregate retail buyer-initiated (seller-initiated) number of shares of stock i on day j. According to Regulation National Market System in 2005, retail investors' orders receive subpenny price improvement, but institutional investors' orders do not. Based on these institutional arrangements, retail buyer (seller) orders tend to be executed slightly above (below) the round penny. In contrast, institutional investors' orders often are executed in the midpoint of the prevailing bid and ask prices. If the bid-ask spread is an odd (even) number of pennies, the resulting midpoint trade price ends in a half-penny (round penny). Specifically, for all trades with an exchange code "D" in the TAQ, let $P_{i,j}$ be the transaction price of stock i in dollars on day j and let $Z_{i,t} \equiv 100 * mod(P_{i,t}, 0.01)$, where $Z_{i,t} \in [0, 1)$ be the fraction of a penny associated with that transaction price. A trade is defined as a retail buy transaction if $Z_{i,t}$ is in the interval $(0.6, 1)$, and the trade is defined as a retail sell transaction if $Z_{i,t}$ is in the interval $(0, 0.4)$. Boehmer et al. (2021) show that the identification of retail investor trading using this method is valid after 2009.

[2]In the U.S., most marketable equity trades initiated by retail investors are executed by wholesalers or via internalization. In other words, these orders are filled from a broker's own inventory. According to Financial Industry Regulatory Authority (FINRA) rules, broker-dealers must publicly report these price-improved off-exchange transactions to a Trade Reporting Facility (TRF). These TRF executions are then included in the TAQ "consolidated tape" of all reported transactions with exchange code "D" (Boehmer et al. 2021).

We then annualize retail investor order imbalance as $FSIS\_OIB_{i,j}$ using the following equation:

$$FSIS\_OIB_{i,t} = 250 \times \frac{\sum_{j=1}^{N} OIB_{i,j}}{N} \tag{6}$$

where 250 is the approximate number of trading days within a fiscal year and N is the number of non-missing $OIB_{i,j}$ over the year. $FSIS\_OIB_{i,j}$ is treated as missing if N is less than 100.

3.3.3. Tone of earnings conference call transcripts

Previous literature ascertains that conference calls have become increasingly important as a venue for firm-specific information dissemination, allowing managers to provide supplementary information on their firms' earnings announcements and granting investors an opportunity to ask questions on both disclosed financial results and expected future performance (e.g., Price et al. 2012, Blau et al. 2015, Brochet et al. 2018). Price et al. (2012) report that the tone of earnings conference call discussion is significantly related to abnormal returns and trading volume over 2004–2007. Jiang et al. (2019) pinpoint that the sentiment measure based on the tone of earnings conference calls is complementary to the existing measures of investor sentiment.

Our third proxy for FSIS is based on quarterly non-political sentiment ($NPSentiment_{i,q}$) from Hassan et al. (2019) who apply a pattern-based sequence-classification method of computational linguistics to analyze firms' earnings conference call transcripts. Hassan et al. (2019) first construct a non-political training library for the topics related to "performance", "ownership changes", or "corporate actions" to identify two-word combinations (bigrams), using newspaper articles published in the Wall Street Journal, New York Times, USA Today, and Washington Post from Factiva. They then count the number of instances of bigrams indicating the discussions of a given non-political topic in earnings conference call transcripts, in conjunction with positive and negative words as defined by Loughran & McDonald (2011). We define the third proxy for FSIS ($FSIS\_ECS_{i,j}$) as the sum of $NPSentiment_{i,q}$ over a fiscal year:

$$FSIS\_ECS_{i,t} = \sum_{q=1}^{4} NPSentiment_{i,q} \tag{7}$$

3.4. Baseline regression

To investigate the empirical relation between FSIS and firm productivity, we estimate the following baseline regression:

$$TFP_{i,t} = \beta_0 + \beta_1 FSIS_{i,t} + B\,Controls_{i,t} + \mu_t + \theta_j + \varepsilon_{i,t} \tag{8}$$

where i is firm index, t is year index, and j is industry index. *TFP* is measured by İmrohoroğlu & Tüzel's (2014) total factor productivity. *FSIS* is one of the three sentiment measures (*FSIS_OR*, *FSIS_OIB*, and *FSIS_ECS*).

The first control variable in *Controls* is Baker & Wurgler's (2006) sentiment index (*BWI*), which controls for the potential impact of market-level investor sentiment on firm productivity. Following Bennett et al. (2020), we also include the natural logarithm of total assets (*Assets*), Tobin's Q (Q), cash scaled by total assets (*Cash*), debt scaled by total assets (*Debt*), research and development expenses scaled by total assets (*R&D*), and capital expenditure scaled by total assets (*Capex*) in *Controls*. Since *TFP* may be associated with other observable firm characteristics, such as firm age, business risk, and diversification (e.g., İmrohoroğlu & Tüzel 2014, Loderer et al. 2016, Bennett et al. 2020), we further include *Firm_Age*, *Business_Risk*, and *Diversified* in *Controls*. To control for the variations of firm productivity across different industries and over time, we include the year fixed effects (μ_t) and Fama-French 48 industry fixed effects (θ_j) in the baseline regression.

All accounting variables in dollars are inflation-adjusted to 2019 dollars. All variables are winsorized at the top and bottom one percent of their distributions, except for *Firm_Age* and indicator variable *Diversified*. To facilitate comparability among sentiment proxies derived from different methodologies and the interpretation of estimated results, we standardize the three FSIS proxies by subtracting the mean and dividing by the standard deviation. Therefore, the coefficient on *FSIS* (β_1) can be interpreted as the change in a firm's productivity in response to a one-standard-deviation change in *FSIS*. The detailed definition of all variables is provided in Appendix A.

4. Main results

4.1. Descriptive statistics

Table 1 presents the descriptive statistics of the variables used in our baseline regression. The mean value of *TFP*, measured by the natural logarithm of total factor productivity, is -0.318, with a standard deviation of 54.4%. All investor sentiment variables are standardized with a mean of zero and a standard deviation of one. The medians of the FSIS measures, *FSIS_OR*, *FSIS_OIB*, and *FSIS_ECS*, are 0.017, 0.098, and -0.025, respectively. The median value of market-level investor sentiment, *BWI*, is 0.108. The average firm size, measured by the natural logarithm of total assets is 6.922. On average, our sample firms have an average Q of 1.955, indicating that an average firm's market value is approximately two times higher than its book value of assets. The average cash holdings of our sample firms account for 17.9% of total assets. Moreover, the mean values of *Debt*, *R&D*, and *Capex* are 23.1%, 5.0%, and 4.8%, respectively. The average age of our sample firms is 24 and 53.7% of our sample firms have multiple segments. The distributions of these variables are generally comparable to those reported in previous studies.

4.2. Baseline regression results

Table 2 presents the estimated coefficients of our baseline regression (Equation (8)). Columns (1)–(3) show that the coefficients of the three FSIS proxies are all positive and statistically significant at the 1% level, after controlling for firm characteristics that may influence firm productivity as well as the year and industry fixed effects. Beyond their statistical significance, our baseline regression results are also economically meaningful, reporting that a one-standard-deviation increase in *FSIS_OR*, *FSIS_OIB*, and *FSIS_ECS* is associated with a 2.8%, 1.6%, and 7.1% increase in firm productivity, respectively. In terms of the control variables, the coefficients of *BWI* are statistically insignificant, indicating that market-level investor sentiment lacks the power to explain firm-level productivity in our regression specification. The coefficients of *Assets*, Q, and *Cash* are positive and statistically significant. The positive coefficients of these three control variables are consistent with the notion that firms with a larger size, greater future growth opportunities, and higher cash holdings have higher total factor productivity. The coefficients of *R&D*, *Firm_Age*, and *Diversified* are all negative and statistically significant, indicating that firms with more R&D investment, older firm age, and more diversified business segments tend to have lower total factor productivity. The signs of our control variables are generally in line with the findings in İmrohoroğlu & Tüzel (2014) and Bennett et al. (2020).

4.3. Endogeneity

The aforementioned baseline regression results show that investor sentiment is positively associated with firm productivity. However, our estimation involves potential endogeneity concerns that firms with high productivity are likely to attract investors' attention, leading to higher FSIS. Endogeneity concerns also rise if unobservable firm characteristics have a confounding effect on both investor sentiment and firm productivity. To address these endogeneity concerns, we adopt the following three identification strategies: a difference-in-differences (DID) model, a high-dimensional fixed-effect model, and FSIS measured at time $t-1$ and as its change form.

4.3.1. Difference-in-Differences analysis

Previous studies treat a firm's addition to the S&P 500 index as an exogenous event and examine the impact of S&P 500 index addition on the firm's stock returns (e.g., Shleifer 1986, Harris & Gurel 1986, Beneish & Whaley 1996, Chen et al. 2005) and corporate policies (e.g., Brisker et al. 2013, Huseynov et al. 2017). More recent studies use the Russell 1000 index reconstitution as a source of exogenous variation in firms' ownership structure (e.g., Chang et al. 2015, Boone & White 2015, Fich et al. 2015) and explore the impact of the index reconstitution on corporate payout policy (Crane et al. 2016), corporate tax planning (Chen et al. 2019), and small firm financing (Cao et al. 2019). Since the selection of both the S&P and the Russell indices' constituents is at the discretion of the Index Committees and based on several eligibility factors, such as market capitalization, firms selected in the indices have little control on the selection process.[3] When a firm is added to an index, index-tracking

[3]Please refer to S&P U.S. Indices Methodology and Russell U.S. Equity Indices for the detailed discussions on the construction methodologies of these two indices.

funds are obligated to purchase the firm's stock, leading to a positive drift of the firm's stock return around the addition announcement event. Such a positive drift may attract investor awareness (Chen et al. 2005), especially the attention-triggered retail investors. Given that the addition to the S&P 500 index or the Russell 1000 index does not change a firm's production and operation, we argue that the index addition has a positive impact on the firm's FSIS but does not directly affect its productivity.

Following Bennett et al.'s (2020) research design, we first verify the effect of index additions on FSIS. We define two indicator variables, *Addition_S&P* and *Addition_Russell*, which are equal to one if a firm is added to the corresponding S&P 500 index or Russell 1000 index in the previous three years including the year of the addition and zero otherwise. We then regress our FSIS proxy variables on these two indicator variables and control for *BWI*, *Assets*, *Q*, and *Firm_Age*. We only focus on firms with above the annual median of total assets in this test, because it is unlikely that small firms are added to the two indices due to the market capitalization eligibility factor (Bennett et al. 2020). The estimation results are presented in Table 3. The dependent variables are *FSIS_OR* in columns (1) and (4), *FSIS_OIB* in columns (2) and (5), and *FSIS_ECS* in columns (3) and (6), respectively. The coefficients of *Addition_S&P* and *Addition_Russell* are all positive and statistically significant, apart from column (5), indicating that FSIS increases when firms have been added to the S&P 500 index or Russell 1000 index during the previous three years.

Next, we conduct a DID analysis and investigate whether the increase in FSIS due to index additions is associated with an increase in total factor productivity. To construct our DID sample for the S&P 500 index additions, we employ a propensity score matching (PSM) technique to find the control firms that are comparable to the treated firms which are newly included in the S&P 500 index over our sample period. Following Bennett et al. (2020), we require that control firms have Compustat data available and have never been included in the S&P 500 index during our sample period. Using the firm characteristics controlled in our baseline regression (*Assets*, *Q*, *Cash*, *Debt*, *R&D*, *Capex*, *Firm_Age*, *Business_Risk*, and *Diversified*) as the matching criteria and the minimum Mahalanobis distance matching method, we match treated firms to control firms within the same two-digit SIC industries. Similarly, we construct our DID sample for the Russell 1000 index additions. Our DID samples cover firm-year observations three years before and three years after a firm's index addition, including the year of the addition. We require that the firms in this test have three years of financial data before and after the index addition.

Using these two DID samples, we first conduct parallel trend analyses of the relation between index additions and TFP:

$$\begin{aligned} TFP_{i,t} = \alpha + \beta_{-3} * Addition\_{-3}Y_{i,t} + \beta_{-2} * Addition\_{-2}Y_{i,t} + \beta_{-1} * Addition\_{-1}Y_{i,t} + \beta_0 * \\ Addition\_0Y_{i,t} + \beta_1 * Addition\_1Y_{i,t} + \beta_2 * Addition\_2Y_{i,t} + \beta_3 * Addition\_3Y_{i,t} + \mu_t + \varepsilon_{i,t} \end{aligned} \tag{9}$$

where the dependent variable is $TFP_{i,t}$ and the independent variables are seven dummy variables indicating the time relative to the index addition. $Addition\_nY_{i,t}$ is equal to one if firm i is a treated firm and year t is n years away from firm i's index addition year, and zero otherwise. For example, $Addition\_0Y_{i,t}$ refers to the index addition year and $Addition\_{-3}Y_{i,t}$ refers to the third year before the index addition year. If firm i is a control firm, these seven dummy variables are equal to zero. Following Bennett et al. (2020), we control for the year fixed effects.

Panels A and B of Figure 1 display the results of our parallel trend analyses in Equation (9). The vertical axis plots the estimated coefficients (β_n) and the horizontal axis shows the number of years relative to the index addition events (n). The dashed lines are for the 90% confidence intervals of the estimated coefficients, and the confidence intervals are constructed based on standard errors clustered at the firm level. Panels A and B show that β_{-3}, β_{-2}, and β_{-1} are statistically insignificant at the 10% level, suggesting that there is not a statistically significant difference in TFP between the treated and control firms over a three-year window before the index additions. The parallel trend condition is satisfied in our two DID samples. Panels A and B also show that β_1, β_2, and β_3 are positive and statistically significant at the 10% level, implying that treated firms' TFP is significantly higher than control firms' TFP over a three-year window after the index additions.

We further use the DID samples to estimate the following specification:

$$TFP_{i,t} = \beta_0 + \beta_1 Treat\_S\&P_i (or\ \ Treat\_Russell_i) \times Post_{i,t} + \beta_2 Post_{i,t} + B \times Controls_{i,t} + \mu_t + \gamma_i + \varepsilon_{i,t} \tag{10}$$

where i is firm index, t is year index, $Treat\_S\&P_i$ ($Treat\_Russell_i$) is equal to one if firm i is added in the S&P 500 (Russell 1000) index and zero otherwise, $Post_{i,t}$ is equal to one if year t is either an index addition year or after the index addition and zero otherwise, $Controls_{i,t}$ are the control variables in Table 2, μ_t is the year fixed effects, and γ_i is the firm fixed effects. Table 4 shows the estimation results of Equation (10). In columns (1) and (2), the coefficients of the interaction terms, $Treat\_S\&P_i \times Post_{i,t}$ and $Treat\_Russell_i \times Post_{i,t}$, are all positive and statistically significant at the 5% level, indicating that firms become more productive after being added to the S&P 500 index or Russell 1000 index. Since we have shown that the index additions place a positive and exogenous shock on FSIS, our findings in Table 4 justify a causal relation between FSIS and TFP.

4.3.2. High-dimensional fixed effects

Confounding variables, correlated with both FSIS and TFP but unobservable to econometricians, may lead to estimation bias and preclude causal inference in our study. To address the endogeneity concern due to omitted variables, we follow Gormley & Matsa's (2014) advice and adopt a high-dimensional fixed effects model. Specifically, we control for unobservable heterogeneity across firms and time-varying heterogeneity across industries in our baseline regressions. Table 5 presents the estimation results of our baseline regression after controlling for the firm fixed effects and Fama-French 48 industry × year fixed effects. In columns (1)–(3), the coefficients of our three FSIS proxy variables are all positive and statistically significant at the 1% level, suggesting that a one-standard-deviation increase in *FSIS_OR*, *FSIS_OIB*, and *FSIS_ECS* leads to 1.8%, 1.2%, and 6% increase in firm productivity, respectively. The positive relation between FSIS and TFP remains robust after controlling for unobserved heterogeneity.

4.3.3. Change in FSIS and lagged FSIS

Our baseline regression results may be subject to the concerns of reverse causality and simultaneity. If sentimental investors get attracted by firms with high productivity, FSIS and TFP are contemporaneously linked. In this case, FSIS follows TFP instead of facilitating TFP. To rule out this alternative explanation, we investigate the responsiveness of the change in TFP to the change in FSIS and the impact of one-year lagged FSIS on TFP. Panel A of Table 6 shows that the estimated coefficients of the change in FSIS proxy variables are all positive and statistically significant at the 1% level, supporting the narrative that the change in FSIS is positively related to the change in TFP. Panel B of Table 6 shows that the estimated coefficients of the lagged FSIS proxy variables are all positive and statistically significant at the 5% and 1% levels, which mitigates the simultaneity concern.

Collectively, the results discussed in Sections 4.3.1–4.3.3 suggest that firms with higher FSIS, on average, enjoy a higher TFP.

4.4. Mechanisms

In this section, we explore the following four potential mechanisms through which FSIS affects TFP: sentiment spillover, managers catering, external financing, and innovation efficiency.

4.4.1. Sentiment spillover

High FSIS may increase employees' morale, which influences their perceptions of future firm growth, their own incentives, and ultimately their production efficiency. McLean & Zhao (2014) provide empirical evidence that a firm's investment and employment are less sensitive to its future growth opportunities during low market-level investor sentiment periods. Dang & Xu's (2018) model also shows that manager's sentiment is positively related to investor sentiment, therefore managers' perceptions of returns on R&D investments and willingness to invest in innovation rise with investor sentiment. Recent studies show that the adoption of automation technology not only reduces workers' wage bargaining power and incentives but also affects firms' finance policy (David & Dorn 2013, Graetz & Michaels 2017, Acemoglu & Restrepo 2020). Since it is unlikely that FSIS affects firms' automation production process, we expect that the positive effect of FSIS on TFP is more pronounced for firms with lower exposure to automation technology and relying more on human labor in their production process.

Mann & Püttmann (2018) classify an automation patent as "a device that carries out a process independently", where the "device" refers to a physical machine, a combination of machines, an algorithm, or a computer program that automates a production process without human intervention except for supervision. Using the data from automation patent textual analysis in Mann & Püttmann (2018), we follow Qiu et al. (2020) and measure the automation exposure, *Auto_Expo*, as the natural logarithm of the segment-sales-weighted sum of the stock of automation patents across all four-digit SIC industries. Given that the data on automation patents are only available to us until 2014, the sample period for our analysis based on automation patents spans 2010 to 2014.

We define two dummy variables, *D_High* and *D_Low*, which indicate whether a firm's $Auto\_Expo_t$ is above or below the annual sample median. Then we extend our baseline regression by interacting our FSIS proxy variables with *D_High* and *D_Low*. The estimated regression coefficients are presented in columns (1)–(3) of Table 7. The coefficients of the interaction terms, *FSIS*×*D_Low*, are all positive and statistically significant at the 1% level. The coefficients of *FSIS*×*D_Low* are all larger than the corresponding coefficients of *FSIS*×*D_high*. The F-statistics of the equality tests on the coefficients show that the difference in the coefficients between *FSIS*×*D_Low* and *FSIS*×*D_high* is statistically significant in columns (2) and (3), suggesting that the positive effect of FSIS on TFP is more pronounced for firms with a lower automation exposure. Overall, these results are consistent with our expectation that high FSIS has a spillover effect on employees' morale, leading to higher productivity for firms with less automated production.

4.4.2. Managers catering

When investors show optimism on firms, managers with higher firm ownership may have an incentive to cater for investors' expectations and improve the productivity of their firms. Better firm operating performance helps maintain positive stock returns so that managers' wealth tied with their firms will also increase. Previous studies show that managers tend to undertake ambitious investment projects that cater for optimistic market expectations of future firm growth opportunities (Polk & Sapienza 2008). In addition, managers with higher firm ownership are more incentivized to overinvest when investors are optimistic about their firms (Grundy & Li 2010). Based on these findings, we conjecture that the positive relation between TFP and FSIS is stronger among firms with higher managerial ownership.

To test this possibility, we measure managerial ownership, *Top5_Own*, as the common stock ownership of the five executives with the highest compensation, including chief executive officers (Kim & Lu 2011). We assign the value of one or zero to *D_High* and *D_Low* based on the annual median of $Top5\_Own_t$. Similarly, we extend our baseline regression by interacting our FSIS proxy variables with the two indicators of managerial ownership. Columns (4)–(6) of Table 7 show that the coefficients of $FSIS \times D\_high$ are all positive and statistically significant at the 5% and 1% levels. The coefficients of $FSIS \times D\_high$ are larger than those of $FSIS \times D\_low$. The F-statistics of equality tests indicate that the difference in the coefficients of the two interaction terms is statistically significant in columns (4)–(6). Our findings suggest that managers with higher firm ownership have a stronger incentive to enhance firm productivity when FSIS is higher.

4.4.3. External financing

With an increase in FSIS, investors have a more optimistic expectation about a firm's future cash flows, which may consequently reduce the cost of external financing and help the firm improve its productivity. Dong et al. (2012) show that firms are more likely to raise capital when the market sentiment is high. External funding provided by sentiment-driven investors may help firms with financial constraints to increase their productivity. Butler & Cornaggia (2011) find that corn productivity increases in response to an ethanol-induced increase in the demand for corn, and the productivity improvement is stronger in counties with better access to external finance. In the same vein, Krishnan et al. (2015) provide evidence that TFP improves following an increase in access to bank financing and the improvement of TFP is significantly larger for financially constrained firms. If FSIS affects TFP through an external financing mechanism, we would expect the positive relation between FSIS and TFP to be more pronounced among financially constrained firms.

To examine the external financing mechanism, we use the *KZ*-index developed by Kaplan & Zingales (1997) as a measure of financial constraint. Firms with a higher *KZ*-index are more likely to experience difficulties when financial conditions tighten. We define *D_High* and *D_Low* indicating whether a firm's *KZ*-index is above or below the annual median. As shown in columns (7)–(9) of Table 7, the coefficients of $FSIS \times D\_high$ are all positive and statistically significant at the 1% level. The coefficients of $FSIS \times D\_high$ are larger than those of $FSIS \times D\_low$. The F-statistics of equality tests show that the difference in the coefficients of the two interaction terms is statistically significant in columns (7)–(9). These results support the external financing mechanism through which sentiment-driven investors enable financially constrained firms to improve productivity.

4.4.4. Innovation efficiency

Investors with high sentiment may encourage a firm to engage in innovation activities and improve productivity. On the one hand, Kogan et al. (2017) find that firms with more innovative outputs experience an increase in their productivity. On the other hand, Dang & Xu (2018) show that market sentiment tends to induce higher efficiency in patent production, resulting in a larger quantity and better quality of patents. If sentiment-driven investors incentivize firms to achieve higher productivity through the innovation mechanism, we predict that the positive relation between FSIS and TFP is more pronounced among firms with higher innovation efficiency.

Following the literature (Shea 1999, Dang & Xu 2018), we construct a measure of innovation efficiency using the ratio of patents to R&D spending, *Patent/R&D*. We then assign the value of one to *D_High* (*D_Low*) if *Patent/R&D* is above (below) the annual median, and zero otherwise. Columns (10)–(12) of Table 7 show that the coefficients of *FSIS*$\times$*D_high* are positive and statistically significant at the 5% and 1% levels. The coefficients of *FSIS*$\times$*D_high* are larger than those of *FSIS*$\times$*D_low*. The F-statistics of equality tests indicate that the difference in the coefficients of the two interaction terms is statistically significant in columns (10) and (12), which supports our prediction that innovation stimulated by FSIS leads to an increase in TFP.

5. Supplementary test results

In this section, we first assess whether our results are robust to alternative measures of TFP. Second, we test the persistence of the impact of FSIS on TFP. Third, we extend our sample period to 1992–2019 for *FSIS_OR* and 2002–2019 for *FSIS_ECS*. Lastly, we explore the relationship between FSIS and firm operational efficiency.

5.1. Alternative measures of productivity

To evaluate whether our finding is sensitive to the measure of firm productivity, we use two alternative proxies for total factor productivity and replicate our baseline regression. The first alternative measure of TFP, *TFP_Alt1*, is constructed by the estimation method of Ackerberg et al. (2015) that addresses the potential endogeneity issue in estimating the production function. The second alternative measure of TFP, *TFP_Alt2*, is estimated by Jacob (2021)'s specification. The detailed estimation process of these two proxies for productivity is provided in Appendix B. Table 8 presents the results of our baseline regression using these two alternative measures of TFP. The dependent variable is TFP_Alt1_t in columns (1)–(3) and TFP_Alt2_t in columns (4)–(6). The estimated coefficients of three FSIS proxy variables are positive and statistically significant at the 5% and 1% levels. Overall, these results confirm that our main finding is robust to alternative estimations of firm productivity. Neither of the two alternative measures of TFP has an economically or statistically material impact on our main finding.

5.2. Persistence of FSIS

Previous studies suggest that the impact of sentiment-driven transactions on stock returns is only transitory (e.g., Barber et al. 2009, Dorn 2009, Aboody et al. 2018). In this section, we examine whether FSIS has a permanent impact on TFP or whether the positive relation between FSIS and TFP decreases over time. If the positive relation between FSIS and TFP is driven by confounding firm fundamentals, then it is unlikely that the positive relation gradually diminishes over time. We replace the contemporaneous TFP_t in our baseline regression by one of the three forward terms: TFP_{t+1}, TFP_{t+2}, and TFP_{t+3}. The estimated coefficients are reported in Table 9. The coefficients of *FSIS_OR* and *FSIS_ECS* are all positive and statistically significant in columns (1)–(3) and columns (7)–(9). The coefficients of *FSIS_OIB* are all positive in columns (4)–(6), but only statistically significant in column (4). There exists evidence that the positive impact of FSIS on TFP is persistent in the long term. However, combining the results reported in Table 2 and Table 9, we find that the positive impact of FSIS on TFP decreases over time. The coefficients of *FSIS_OR* monotonically decrease from 0.028 in column (1) of Table 2 to 0.014 in column (3) in Table 9. The coefficients of *FSIS_ECS* also monotonically decrease from 0.071 to 0.034 over four years. The coefficients of *FSIS_OIB* become statistically insignificant in year $t + 2$ and $t + 3$.

5.3. Extended sample period

The sample period of our empirical analyses is 2010–2019, because one of our three FSIS proxy variables, *FSIS_OIB*, is only an effective measure of FSIS for the post-2010 period.[4] To check if the positive relation between FSIS and TFP is robust in a longer sample period, we extend our sample based on the data availability of *FSIS_OR* and *FSIS_ECS*. Specifically, our extended sample period for *FSIS_OR* starts from 1992 when the CRSP started to provide daily opening stock price data, and our extended sample period for *FSIS_ECS* starts from 2002 when Hassan et al.'s (2019) data on the transcripts of earnings conference calls are available. Using these two extended samples, we re-estimate our baseline regression reported in Table 2 and the regression specifications reported in Panels A and B of Table 6. We tabulate the regression results in Table 10. All the estimated coefficients of FSIS proxy variables are positive and statistically significant at the 1% level. Our core evidence remains robust in the two extended samples.

5.4. FSIS and operational efficiency

Lastly, we investigate the relation between FSIS and other measures of operational efficiency. Following previous studies on firm operational efficiency and profitability (Alimov & Mikkelson 2012, Loderer et al. 2016), we employ the operating cost ratio (*Sale/Cost*) and asset turnover ratio (*Asset_Turnover*) as the proxies for operational efficiency. *Sale/Cost* is defined as the ratio of sales to total costs. *Asset_Turnover* is measured by the ratio of sales to the lagged net assets. We also adopt the return on asset (*ROA*) and net income dummy (*Negative_NI*) as the proxies for operational performance. *ROA* is the ratio of operating income before depreciation to the lagged total assets. *Negative_NI* is defined as a dummy variable that is equal to one if a firm's net income is negative and zero otherwise. We replicate the baseline regression in Table 2 by replacing *TFP* with the alternative

[4]Please refer to Boehmer et al. (2021) for the details of the sub-penny price improvement to retail investors.

efficiency measures.

Table 11 shows the estimation results. In columns (1)–(3), the dependent variable is $Sale/Cost_t$, and the estimated coefficients of three FSIS proxy variables are all positive and statistically significant at the 1% level. The dependent variable in columns (4)–(6) is *Asset_Turnover*, and the estimated coefficients are positive and statistically significant. ROA_t is employed as the dependent variable in columns (7)–(9), and the coefficients on FSIS proxy variables are all positive and statistically significant at the 1% level. Columns (10)–(12) use the loss dummy, $Negative\_NI_t$, as the dependent variable. The coefficients are all negative and statistically significant at the 1% level. Overall, these findings corroborate our main finding that FSIS improves firms' operational efficiency.

6. Conclusion

At the corporate level, productivity is a measure of the efficiency of a company's production process. It remains unknown whether the high sentiment of investors in the financial market has any spillover effect on employees' morale and managers' incentives, which in turn may affect firm productivity. It is also an open question whether high investor sentiment can improve productivity through influencing corporate activities, such as external financing and innovation, which have been shown by the previous literature as the drivers of cross-sectional differences in productivity. Our study closes this gap by providing strong empirical support for the hypothesis that FSIS is positively associated with firm productivity.

We address endogeneity concerns using three identification methods: a DID framework utilizing a stock's index addition as an exogenous shock on its FSIS, a high-dimensional fixed effects model, and model specifications estimating the impact of the change in FSIS on the change in TFP and the impact of one-year lagged FSIS on TFP. In our further analyses, we show that the positive impact of FSIS on firm productivity is stronger for firms with less exposure to automated production, more managerial ownership, tighter financial constraints, and higher innovative efficiency. Moreover, we find that high FSIS facilitates an increase in firms' operational efficiency and profitability. Our findings support the view that when FSIS is high, investors tend to hold optimistic expectations of firms' future performance, which encourages firms to be more productive.

Overall, our findings highlight that investor sentiment, as a behavioral phenomenon in the financial market, has a real effect on firm productivity. Our evidence provides a new perspective on the behavioral role of the financial market in corporate activities and outcomes. Meanwhile, our study calls for another natural avenue to explore: whether an increase in the sentiment of employees and managers makes their own firms more productive. Given that the sentiment of workers and managers is directly related to their morale and incentives, if the firm-level data on employees ans managerial sentiment is available, it will be valuable for researchers to further understand the cross-sectional differences in firm productivity.

Appendix A

Table A1. Variable definitions

This table provides variable definitions and corresponding data sources. IMTU refers to İmrohoroğlu & Tüzel's (2014) website, CRSP refers to the Centre for Research in Security Prices, TAQ refers to the Trade and Quote database, HHLT refers to Hassan et al.'s (2019) website, BW refers to Baker & Wurgler's (2006) website, BEA refers to the Bureau of Economic Analysis' website, KMLP refers to Mann & Püttmann's (2018) website, and USPTO refers to the United States Patent and Trademark Office's website.

Variable	Definition	Source
$y_{i,t}$	Sales minus materials, deflated by the GDP price deflator from the BEA. Sales is Compustat item SALE. Materials is total expenses minus labor expenses, where total expenses is sales minus operating income before depreciation and amortization (Compustat item OIBDP) and labor expenses is the number of employees (Compustat item EMP) multiplying average wages from the Social Security Administration (İmrohoroğlu & Tüzel 2014).	IMTU
$l_{i,t}$	The stock of labor, measured by the number of employees (Compustat item EMP) (İmrohoroğlu & Tüzel 2014).	IMTU
$k_{i,t}$	The stock of capital, measured by gross property, plant, and equipment (Compustat item PPEGT), deflated by the price deflator for private fixed investment from the BEA, following the methods of Hall (1990) and Brynjolfsson & Hitt (2003). Average age of capital stock is calculated as the ratio of accumulated depreciation (PPEGT-Net PPE, Compustat item DPACT) to current depreciation (Compustat item DP). Age is smoothed by taking a 3-year moving average. The capital stock is lagged by one period to measure the available capital stock at the beginning of the period (İmrohoroğlu & Tüzel 2014).	IMTU
TFP_t	Total factor productivity, a measure of firm-level overall effectiveness and efficiency of using capital and labor in the production process (İmrohoroğlu & Tüzel 2014).	IMTU
$FSIS\_OR_t$	Firm-specific investor sentiment measured by overnight returns, defined as 250 × the average daily overnight returns over fiscal year t (Aboody et al. 2018). $FSIS\_OR$ is standardized to have a mean of zero and standard deviation of one.	CRSP

Continued on next page

Table A1 - continued from previous page

Variable	Definition	Source
$FSIS\_OIB_t$	Firm-specific investor sentiment measured by retail investor order imbalance, defined as $\frac{250}{N} \times \sum_{i=1}^{N} \frac{\text{num. of buyer initiated trades}_i - \text{num. of seller-initiated trades}_i}{\text{num. of buyer-initiated trades}_i + \text{num. of seller-initiated trades}_i}$, where N is the number of non-missing data in fiscal year t (Boehmer et al. 2021). *FSIS_OIB* is standardized to have a mean of zero and standard deviation of one.	TAQ
$FSIS\_ECS_t$	Firm-specific investor sentiment measured by non-political sentiment, defined as the sum of quarterly non-political sentiment in a firm's earnings conference call transcripts over fiscal year t (Hassan et al. 2019). *FSIS_ECS* is standardized to have a mean of zero and standard deviation of one.	HHLT
BWI_t	The sum of Baker & Wurgler's (2006) monthly market sentiment index over fiscal year t. BWI is standardized to have a mean of zero and standard deviation of one.	BW
$Assets_t$	The natural logarithm of total assets (Bennett et al. 2020).	Compustat
Q_t	Tobin's Q, defined as the book value of total assets plus the market value of equity minus the book value of equity divided by the book value of total assets (Bennett et al. 2020).	Compustat
$Cash_t$	Cash and cash equivalent, scaled by total assets (Bennett et al. 2020).	Compustat
$Debt_t$	Total debt, scaled by total assets (Bennett et al. 2020).	Compustat
$R\&D_t$	R&D expenses, scaled by total assets. *R&D* is equal to zero if an observation is missing (Bennett et al. 2020).	Compustat
$Capex_t$	Capital expenditures, scaled by total assets.	Compustat
$Firm\_Age_t$	The number of years since a firm is recorded for the first time in Compustat.	Compustat
$Business\_Risk_t$	The standard deviation of a firm's daily stock returns over year $t-1$ (Bennett et al. 2020).	CRSP
$Diversified_t$	An indicator variable, which is equal to one if a firm has multiple segments reported in the Compustat Historical Segment database and zero otherwise (Bennett et al. 2020).	Compustat
$Addition\_S\&P_t$	An indicator variable, which is equal to one if a firm is added to the S&P 500 index in previous three years including the year of addition and zero otherwise.	CRSP
$Addition\_Russell_t$	An indicator variable, which is equal to one if a firm is added to the Russell 1000 index in previous three years including the year of addition and zero otherwise.	FTSE/Russell
$Addition\_Year_t$	An indicator variable, which is equal to one if a firm is added to the S&P 500 index or Russell 1000 index in fiscal year t and zero otherwise.	CRSP and FTSE/Russell
$Auto\_Expo_t$	Automation patents used in a firm's production process without human intervention (Mann & Püttmann 2018).	KMLP
$Top5\_Own_t$	Managerial ownership, measured by the common stock ownership of the five executives with the highest compensation, including CEO (Kim & Lu 2011).	ExecuComp

Continued on next page

Table A1 - continued from previous page

Variable	Definition	Source
$KZ\text{-}Index_t$	Kaplan & Zingales's (1997) index of financial constraints.	CRSP and Compustat
$Patent/R\&D_t$	Innovation efficiency, defined as the ratio of the number of patents to R&D expenses (Shea 1999).	USPTO and Compustat
TFP_Alt1_t	Firm-level TFP define by Bennett et al. (2020).	BEA and Compustat
TFP_Alt2_t	Firm-level TFP defined by Jacob (2021).	BEA and Compustat
$Sales/Cost_t$	Operational efficiency, defined as the ratio of net sales to total costs, where total costs are sales minus EBITDA (Alimov & Mikkelson 2012).	Compustat
$Asset\_Turnover_t$	Asset turnover, defined as the ratio of sales to the lagged net assets, where net assets equal total assets minus cash (Alimov & Mikkelson 2012).	Compustat
ROA_t	Return on assets, defined as the ratio of operating income before depreciation to the lagged total assets (Loderer et al. 2016).	Compustat
$Negative\_NI_t$	An indicator variable, which is equal to one if a firm's net income is negative and zero otherwise (Loderer et al. 2016).	Compustat

Appendix B

In this appendix, we present the definitions of two alternative measures of firm productivity used in our robustness tests.

We construct our first alternative measure of firm productivity, *TFP_Alt1*, based on Bennett et al.'s (2020) setting. We start from the Cobb-Douglas production function:

$$Y = A \cdot K^{\alpha} \cdot L^{\beta} \qquad (A1)$$

where Y is firm output, K is capital, L is labor, and A is firm productivity. Taking the natural logarithm on both sides of Equation (A1), we get:

$$\ln(Y) = \alpha \cdot \ln(K) + \beta \cdot \ln(L) + \ln(A) \qquad (A2)$$

To calculate a firm's TFP (*ln(A)*), we estimate the following specification:

$$\ln(Y) = \beta_0 + \alpha \cdot \ln(K) + \beta \cdot \ln(L) + \epsilon \qquad (A3)$$

where β_0 is the intercept and ϵ is the residual. Comparing Equation (A2) to (A3), a firm's TFP is the sum of the intercept and residual from Equation (A3):

$$\ln(A) = \beta_0 + \epsilon \qquad (A4)$$

In Equation (A3), Y is firm output or value added, defined as *Sales* minus *Materials* deflated by the GDP deflator from BEA. *Sales* is revenues (Compustat item REVT) and *Materials* is *Total expense* minus *Labor expense*. *Total expense* is defined as the difference between revenues and operating income before depreciation and amortization (Compustat item OIBDP). Different from İmrohoroğlu & Tüzel (2014), *Labor expense* is measured by employee wages (Compustat item XLR). If XLR is missing, we replace it by the product of a firm's employee number (Compustat item EMP) and the average wage per employee in the firm's Fama-French 12 industry. K is capital, defined as the gross property, plant, and equipment (Compustat item PPEGT) deflated by the price deflator for private fixed investment from BEA, followed by the adjustment of the average age of capital (Hall 1990, Brynjolfsson & Hitt 2003). L is labor, defined as the number of employees from Compustat. Following Bennett et al. (2020), we employ the method in Ackerberg et al. (2015) to estimate Equation (A3).

We construct our second alternative measure of firm productivity, *TFP_Alt2*, based on Jacob's (2021) method to estimate production functions. Specifically, *TFP_Alt2* is measured as the residuals from the regressions of value added (firm output) on labor and capital inputs for each industry-year:

$$\ln(\mathit{Value\_Added})_{i,t} = \alpha_0 + \alpha_1 \ln(\mathit{Total\_Wages})_{i,t} + \alpha_2 \ln(\mathit{Fixed\_Assets})_{i,t} + \varepsilon_{i,t} \qquad (A5)$$

where *Value_Added* is defined as earnings before taxed (Compustat items REVT - COGS - XSGA - DP) plus depreciation (Compustat Item DP) and *Total_Wages* (Compustat item XLR). If XLR is missing, we replace it by the product of a firm's employee number (Compustat item EMP) and the average wage per employee in the firm's Fama-French 12 industry. Same as İmrohoroğlu & Tüzel (2014) and Bennett et al. (2020), *Fixed_Assets* is measured by the gross property, plant, and equipment (Compustat item PPEGT) deflated by the price deflator for private fixed investment from the BEA. We follow Hall (1990) and Brynjolfsson & Hitt (2003) to adjust the average age of capital.

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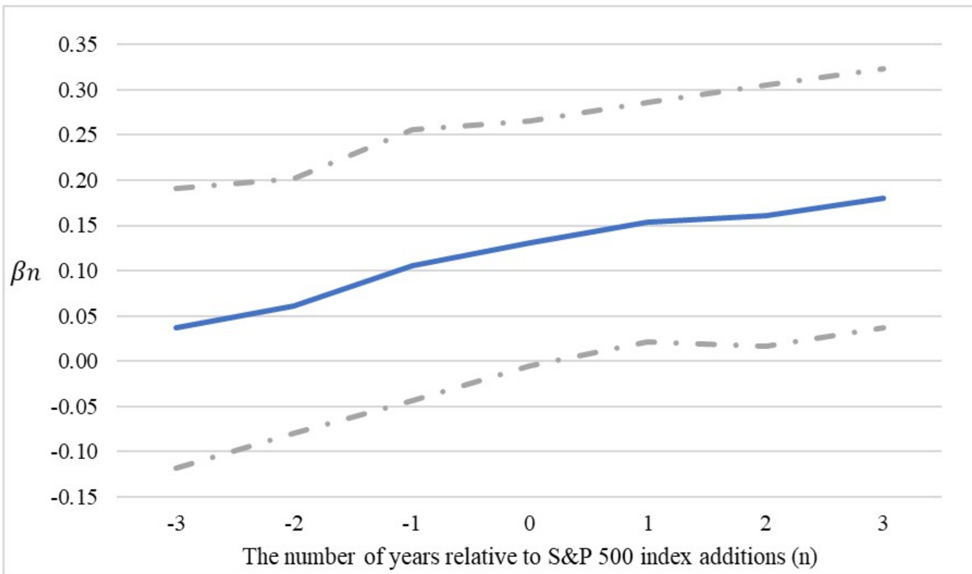
Figure 1. Parallel trend analyses of the effect of index additions on TFP. This figure shows the parallel trend analyses of the effect of index additions on TFP. The sample includes treated firms that are added to the S&P 500 index or Russell 1000 index and control firms matched by firm characteristics which are included as control variables in Equation (8) within the same two-digit SIC industries. The y-axis plots the coefficients estimated by Equation (9) which regresses TFP on dummy variables indicating the year relative to an index addition, controlling for the year fixed effects. The x-axis plots the time relative to the index addition. The dash lines indicate the 90% confidence intervals for the estimated coefficients, and the confidence intervals are based on standard errors clustered at the firm level.

Panel A. S&P 500 index additions



Panel B. Russell 1000 index additions

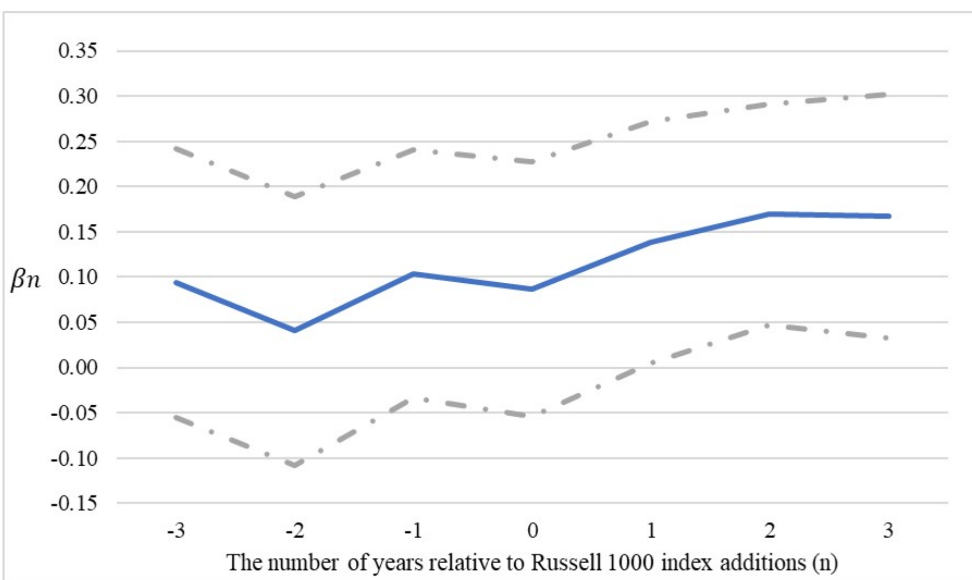


Table 1. Summary statistics

This table reports the summary statistics of the variables used in our baseline regression. Our sample consists of $18,107$ firm–year observations over the fiscal years 2010–2019, with required data for our baseline regressions. The number of observations, mean, standard deviation, 1st percentile, 25th percentile, median, 75th percentile, and 99th percentile are reported from left to right, in sequence for each variable. The three FSIS variables are standardized to have a mean of zero and standard deviation of one. All accounting variables in dollars are inflation-adjusted to 2019 dollars. All control variables are winsorized at the 1% and 99% levels, apart from *Firm_Age* and *Diversified*. All variables are defined in Appendix A.

Variable	Obs.	Mean	S.D.	p1	p25	Median	p75	p99
Dependent variables								
TFP_t	18107	-0.318	0.544	-2.097	-0.576	-0.306	-0.030	1.003
Independent variables of interest								
$FSIS\_OR_t$	15206	0.000	1.000	-4.379	-0.424	0.017	0.474	3.476
$FSIS\_OIB_t$	14835	0.000	1.000	-2.994	-0.539	0.098	0.610	2.511
$FSIS\_ECS_t$	15786	0.000	1.000	-3.165	-0.541	-0.025	0.549	2.866
Control variables								
BWI_t	18107	0.000	1.000	-2.770	-0.245	0.108	0.568	1.289
$Assets_t$	18107	6.922	1.893	3.044	5.570	6.848	8.188	11.349
Q_t	18107	1.955	1.313	0.610	1.157	1.536	2.226	8.054
$Cash_t$	18107	0.179	0.171	0.001	0.047	0.123	0.260	0.720
$Debt_t$	18107	0.231	0.212	0.000	0.031	0.200	0.357	0.926
$R\&D_t$	18107	0.050	0.079	0.000	0.000	0.007	0.075	0.347
$Capex_t$	18107	0.048	0.050	0.003	0.016	0.031	0.060	0.262
$Firm\_Age_t$	18107	23.709	16.345	4.000	11.000	20.000	31.000	68.000
$Business\_Risk_t$	18107	0.068	0.154	0.011	0.019	0.025	0.035	0.899
$Diversified_t$	18107	0.537	0.499	0.000	0.000	1.000	1.000	1.000

Table 2. Baseline regression: FSIS and productivity

This table reports the panel regressions of total factor productivity (TFP) on firm-specific investor sentiment (FSIS) and control variables. The sample consists of U.S. firm–year observations over the sample period 2010–2019, with required data for the regressions. The dependent variable is TFP_t and the independent variables of interest are $FSIS\_OR_t$, $FSIS\_OIB_t$ and $FSIS\_ECS_t$. All variables are defined in Appendix A. The coefficients of the Fama–French 48 industry and year fixed effects are suppressed for brevity in the respective columns. t-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	TFP_t		
Variables	**(1)**	**(2)**	**(3)**
$FSIS\_OR_t$	0.028***		
	[5.93]		
$FSIS\_OIB_t$		0.016***	
		[3.49]	
$FSIS\_ECS_t$			0.071***
			[11.92]
BWI_t	0.006	0.015	0.017
	[0.46]	[1.13]	[1.24]
$Assets_t$	0.144***	0.166***	0.152***
	[26.81]	[29.88]	[28.99]
Q_t	0.075***	0.079***	0.077***
	[10.00]	[10.20]	[10.22]
$Cash_t$	0.177***	0.130**	0.105*
	[2.94]	[2.04]	[1.79]
$Debt_t$	0.001	-0.089**	-0.034
	[0.03]	[-2.06]	[-0.79]
$R\&D_t$	-1.433***	-1.666***	-1.448***
	[-9.04]	[-10.31]	[-9.63]
$Capex_t$	-0.061	0.044	-0.188
	[-0.32]	[0.23]	[-0.94]
$Firm\_Age_t$	-0.002***	-0.002***	-0.002***
	[-4.45]	[-5.09]	[-5.51]
$Business\_Risk_t$	-0.067	0.005	-0.016
	[-1.43]	[0.11]	[-0.35]
$Diversified_t$	-0.074***	-0.054***	-0.067***
	[-4.92]	[-3.61]	[-4.42]
Constant	-1.209***	-1.395***	-1.353***
	[-12.43]	[-14.97]	[-12.63]
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	15,206	14,835	15,786
Adjusted-R^2	0.276	0.334	0.321

Table 3. Index additions and FSIS

This table shows the effect of index additions on FSIS. The sample includes firms with above annual median of total assets. The dependent variables are $FSIS\_OR_t$ in columns (1) and (4), $FSIS\_OIB_t$ in columns (2) and (5), and $FSIS\_ECS_t$ in columns (3) and (6). In columns (1)–(3), the independent variable of interest is $Addition\_S\&P_t$, an indicator variable equal to one if a firm is added to the S&P 500 index in previous three years including the year of the addition, and zero otherwise. In columns (4)–(6), the independent variable of interest is $Addition\_Russell_t$, an indicator variable equal to one if a firm is added to the Russell 1000 index in previous three years including the year of the addition, and zero otherwise. All variables are defined in Appendix A. The coefficients of the Fama–French 48 industry and year fixed effects are suppressed for brevity in the respective columns. t-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$FSIS\_OR_t$	$FSIS\_OIB_t$	$FSIS\_ECS_t$	$FSIS\_OR_t$	$FSIS\_OIB_t$	$FSIS\_ECS_t$
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$Addition\_S\&P_t$	0.027*	0.105**	0.033*			
	[1.80]	[2.24]	[1.70]			
$Addition\_Russell_t$				0.002*	-0.024	0.092**
				[1.73]	[-1.22]	[2.39]
BWI_t	0.012	0.170**	-0.034	0.011***	0.015	0.063
	[0.50]	[2.24]	[-1.34]	[5.67]	[0.61]	[1.42]
$Assets_t$	-0.003	0.106***	0.030***	0.000	0.060***	0.042***
	[-0.91]	[6.91]	[5.99]	[0.21]	[7.80]	[3.55]
Q_t	0.021***	0.099***	0.028***	0.001***	0.024***	0.071***
	[5.53]	[8.14]	[4.72]	[2.58]	[3.90]	[5.27]
$Firm\_Age_t$	-0.001***	0.001	0.001***	-0.000***	0.000	0.004***
	[-4.00]	[0.71]	[3.73]	[-3.49]	[1.00]	[4.99]
Constant	0.070	-0.721***	-0.457***	0.078***	0.064	-0.387***
	[1.31]	[-4.10]	[-5.82]	[28.06]	[1.02]	[-3.60]
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,384	6,879	8,493	8,384	6,879	8,493
Adjusted-R^2	0.110	0.127	0.079	0.033	0.059	0.038

Table 4. DID analyses: Index additions and productivity

This table reports the results of difference-in-differences (DID) tests. The sample includes treated firms added to the S&P 500 index or Russell 1000 index and control firms matched by firm characteristics in the same two-digit SIC industries. For both treated and control firms, the sample covers firm–year observations three years before and after the index additions, including the addition years. The dependent variable is TFP_t. The independent variable of interest is $Treat\_S\&P_i \times Post_{i,t}$ in column (1) and $Treat\_Russell_i \times Post_{i,t}$ in column (2). $Treat\_S\&P_i$ ($Treat\_Russell_i$) is an indicator variable that is equal to one if firm i is added to the S&P 500 (Russell 1000) index and zero otherwise. $Post_{i,t}$ is an indicator variable that is equal to one if year t is either an index addition year or after the index addition and zero otherwise. All variables are defined in Appendix A. The coefficients of the year and firm fixed effects are suppressed for brevity in the respective columns. t-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	TFP_t	
Variables	**(1)**	**(2)**
$Treat\_S\&P \times Post_t$	0.048**	
	[2.03]	
$Treat\_Russell \times Post_t$		0.075**
		[2.40]
$Post_t$	0.005	-0.016
	[0.36]	[-1.26]
BWI_t	0.095***	0.084***
	[3.18]	[3.12]
$Assets_t$	0.024***	0.052***
	[3.74]	[5.42]
Q_t	0.106	0.174
	[0.92]	[1.28]
$Cash_t$	-0.061	-0.104
	[-0.85]	[-1.24]
$Debt_t$	-3.570***	-1.486**
	[-5.00]	[-2.09]
$R\&D_t$	0.442	0.571**
	[1.44]	[2.12]
$Capex_t$	-0.033	-0.045
	[-1.16]	[-1.19]
$Firm\_Age_t$	0.116	-0.118
	[1.13]	[-0.85]
$Business\_Risk_t$	-0.014	0.020
	[-0.51]	[0.86]
$Diversified_t$	0.028	-0.003
	[0.92]	[-0.10]
Constant	0.369	0.590
	[0.36]	[0.51]
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	1,341	1,403
Adjusted-R^2	0.210	0.134

Table 5. High-dimensional fixed effects

This table reports the panel regressions of TFP on FSIS and control variables, controlling for the interacted industry–year and firm fixed effects. The sample consists of U.S. firm–year observations over the sample period 2010–2019, with required data for the regressions. The dependent variable is TFP_t and the independent variables of interest are $FSIS\_OR_t$, $FSIS\_OIB_t$, and $FSIS\_ECS_t$. All variables are defined in Appendix A. The coefficients of the fixed effects are suppressed for brevity in the respective columns. t-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	TFP_t		
Variables	**(1)**	**(2)**	**(3)**
$FSIS\_OR_t$	0.018***		
	[5.78]		
$FSIS\_OIB_t$		0.012***	
		[4.37]	
$FSIS\_ECS_t$			0.060***
			[14.41]
BWI_t	0.008	0.005	0.018*
	[0.89]	[0.52]	[1.87]
$Assets_t$	0.218***	0.228***	0.215***
	[13.78]	[14.86]	[14.19]
Q_t	0.072***	0.077***	0.073***
	[10.72]	[11.14]	[11.07]
$Cash_t$	0.214***	0.162***	0.174***
	[4.30]	[3.33]	[3.41]
$Debt_t$	-0.079	-0.060	-0.040
	[-1.38]	[-1.32]	[-0.74]
$R\&D_t$	-5.052***	-5.026***	-4.921***
	[-13.01]	[-10.91]	[-11.98]
$Capex_t$	0.821***	0.814***	0.803***
	[5.42]	[4.93]	[4.51]
$Firm\_Age_t$	-0.041*	-0.008	0.005
	[-1.91]	[-0.39]	[0.26]
$Business\_Risk_t$	-0.063*	-0.118***	-0.114***
	[-1.89]	[-3.69]	[-3.03]
$Diversified_t$	-0.034*	-0.029	-0.035**
	[-1.82]	[-1.61]	[-2.03]
Constant	-0.736	-1.595***	-1.860***
	[-1.37]	[-2.93]	[-3.86]
Industry × year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Observations	14,748	14,464	15,352
Adjusted-R^2	0.795	0.798	0.797

Table 6. Change in FSIS and lagged FSIS

Panel A. Change in FSIS. This panel reports the panel regressions of the change in TFP (ΔTFP_t) on the change in FSIS ($\Delta FSIS_t$) and the changes in control variables. All variables are defined in Appendix A. The coefficients of the Fama–French 48 industry and year fixed effects are suppressed for brevity in the respective columns. t-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	ΔTFP_t		
Variables	**(1)**	**(2)**	**(3)**
$\Delta FSIS\_OR_t$	0.012***		
	[4.44]		
$\Delta FSIS\_OIB_t$		0.006***	
		[2.60]	
$\Delta FSIS\_ECS_t$			0.036***
			[11.34]
ΔBWI_t	0.001	0.001	0.005
	[0.10]	[0.08]	[0.73]
$\Delta Assets_t$	0.218***	0.230***	0.213***
	[12.71]	[13.62]	[13.43]
ΔQ_t	0.040***	0.047***	0.044***
	[8.29]	[9.27]	[8.93]
$\Delta Cash_t$	0.147***	0.101**	0.087**
	[3.51]	[2.35]	[1.97]
$\Delta Debt_t$	-0.209***	-0.189***	-0.189***
	[-4.69]	[-4.59]	[-4.60]
$\Delta R\&D_t$	-5.463***	-5.940***	-5.577***
	[-13.90]	[-14.86]	[-14.46]
$\Delta Capex_t$	0.661***	0.601***	0.481***
	[4.40]	[4.13]	[2.99]
$\Delta Firm\_Age_t$	-0.010	0.021	0.020
	[-0.62]	[1.16]	[1.21]
$\Delta Business\_Risk_t$	-0.058*	-0.097***	-0.096***
	[-1.70]	[-3.31]	[-2.86]
$\Delta Diversified_t$	-0.033**	-0.031*	-0.032**
	[-1.97]	[-1.89]	[-2.00]
Constant	0.026	-0.022	-0.033
	[1.01]	[-0.71]	[-1.03]
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	12,002	11,904	12,391
Adjusted-R^2	0.150	0.163	0.169

Panel B. Lagged FSIS. This panel reports the panel regressions of TFP_t on the lagged FSIS ($FSIS_{t-1}$) and control variables measured in year t. All variables are defined in Appendix A. The coefficients of the Fama–French 48 industry and year fixed effects are suppressed for brevity in the respective columns. t-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	TFP_t		
Variables	**(1)**	**(2)**	**(3)**
$FSIS\_OR_{t-1}$	0.024***		
	[4.68]		
$FSIS\_OIB_{t-1}$		0.011**	
		[2.32]	
$FSIS\_ECS_{t-1}$			0.054***
			[8.73]
BWI_t	-0.000	0.001	-0.002
	[-0.03]	[0.11]	[-0.18]
$Assets_t$	0.144***	0.163***	0.151***
	[26.19]	[28.59]	[27.96]
Q_t	0.089***	0.088***	0.087***
	[11.24]	[10.83]	[10.81]
$Cash_t$	0.197***	0.160**	0.118*
	[3.14]	[2.39]	[1.91]
$Debt_t$	0.038	-0.047	-0.006
	[0.79]	[-1.04]	[-0.13]
$R\&D_t$	-1.208***	-1.425***	-1.210***
	[-7.38]	[-8.41]	[-7.74]
$Capex_t$	-0.135	-0.035	-0.312
	[-0.67]	[-0.18]	[-1.48]
$Firm\_Age_t$	-0.002***	-0.002***	-0.002***
	[-3.72]	[-4.39]	[-4.85]
$Business\_Risk_t$	-0.062	0.002	-0.007
	[-1.28]	[0.05]	[-0.15]
$Diversified_t$	-0.071***	-0.062***	-0.069***
	[-4.53]	[-3.99]	[-4.31]
Constant	-1.301***	-1.420***	-1.411***
	[-13.11]	[-15.54]	[-13.35]
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	12,507	12,051	12,769
Adjusted-R^2	0.303	0.358	0.333

Table 7. Cross-sectional analyses

This table reports the panel regressions of *TFP* on the interactions between *FSIS* proxy variables and two indicator variables, D_High_t and D_Low_t. We employ $Auto\_Expo_t$ in columns (1)–(3) as the proxy for automation exposure, $TOP5\_Own_t$ in columns (4)–(6) as the proxy for managerial ownership, $KZ\text{-}Index_t$ in columns (7)–(9) as the proxy for financial constraints, and $Patent/R\&D_t$ in columns (10)–(12) as the proxy for innovation. D_High_t (D_Low_t) is equal to one if the corresponding proxy variable is greater than (less than) its annual sample median, and zero otherwise. Control variables are the same as those in Table 2. We only report the coefficients on the interaction terms, and the F-statistic corresponding to a test of equality between interacted coefficients. All variables are defined in Appendix A. The coefficients of the control variables, Fama–French 48 industry fixed effects, and year fixed effects are suppressed for brevity in the respective columns. t-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	TFP_t											
	Auto_Expo			***TOP5_Own***			***KZ-Index***			***Patent/R&D***		
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
$FSIS\_OR_t \times D\_High_t$	0.027***			0.023***			0.038***			0.066***		
	[3.07]			[3.43]			[5.60]			[5.86]		
$FSIS\_OR_t \times D\_Low_t$	0.035***			0.002			0.023***			0.021**		
	[3.48]			[0.37]			[3.60]			[2.13]		
$FSIS\_OIB_t \times D\_High_t$		0.005			0.014**			0.031***			0.021**	
		[0.64]			[2.36]			[4.76]			[2.07]	
$FSIS\_OIB_t \times D\_Low_t$		0.036***			0.001			0.005			0.008	
		[3.62]			[0.29]			[0.77]			[0.82]	
$FSIS\_ECS_t \times D\_High_t$			0.050***			0.049***			0.101***			0.111***
			[4.63]			[7.61]			[12.49]			[10.08]
$FSIS\_ECS_t \times D\_Low_t$			0.096***			0.033***			0.028***			0.042***
			[6.92]			[6.02]			[3.58]			[3.94]
Constant	-1.502***	-1.643***	-1.503***	-0.737***	-0.818***	-0.821***	-1.230***	-1.399***	-1.344***	-1.147***	-1.377***	-1.362***
	[-20.64]	[-25.15]	[-21.00]	[-11.60]	[-13.66]	[-14.02]	[-12.49]	[-14.74]	[-12.13]	[-8.30]	[-11.72]	[-10.99]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-statistics	0.39	5.60**	7.22***	5.35**	3.08*	3.92**	3.00*	8.10***	47.71***	10.37***	1.04	23.87***
Observations	5,986	5,904	6,213	7,672	7,834	7,843	14,195	13,760	14,682	7,572	7,377	7,997
Adjusted-R^2	0.277	0.337	0.331	0.249	0.267	0.292	0.284	0.341	0.327	0.312	0.350	0.362

Table 8. Alternative measures of productivity

This table reports the panel regressions of alternative measures of productivity on *FSIS* and control variables. The dependent variables are TFP_Alt1_t in columns (1)–(3) and TFP_Alt2_t in columns (4)–(6). The detailed estimation process of these two proxies for productivity is provided in Appendix B. The independent variables of interest are standardized $FSIS\_OR_t$, $FSIS\_OIB_t$ and $FSIS\_ECS_t$. The control variables are the same as those in Table 2. All variables are defined in Appendix A. The coefficients of the control variables, year and the Fama–French 48 industry fixed effects are suppressed for brevity in the respective columns. t-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	TFP_Alt1_t			TFP_Alt2_t		
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$FSIS\_OR_t$	0.018***			0.027***		
	[4.18]			[6.45]		
$FSIS\_OIB_t$		0.008**			0.015***	
		[1.97]			[3.44]	
$FSIS\_ECS_t$			0.060***			0.058***
			[11.49]			[10.76]
Constant	-0.168	-0.220**	-0.143	-0.644***	-0.310**	-0.301**
	[-1.60]	[-2.33]	[-1.56]	[-9.97]	[-2.27]	[-2.22]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,902	14,531	15,451	14,110	13,608	14,733
Adjusted-R^2	0.465	0.460	0.459	0.122	0.159	0.147

Table 9. Persistence of the effect of FSIS on TFP

This table reports the panel regressions of foward *TFP* on *FSIS* and control variables. The dependent variables are TFP_{t+1} in columns (1), (4), and (7). The dependent variables are TFP_{t+2} in columns (2), (5), and (8). The dependent variables are TFP_{t+3} in columns (3), (6), and (9). The independent variables of interest are standardized $FSIS\_OR_t$, $FSIS\_OIB_t$ and $FSIS\_ECS_t$. The control variables are the same as those in Table 2. All variables are defined in Appendix A. The coefficients of the control variables, year and the Fama–French 48 industry fixed effects are suppressed for brevity in the respective columns. t-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	TFP_{t+1}	TFP_{t+2}	TFP_{t+3}	TFP_{t+1}	TFP_{t+2}	TFP_{t+3}	TFP_{t+1}	TFP_{t+2}	TFP_{t+3}
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
$FSIS\_OR_t$	0.025***	0.015***	0.014**						
	[5.05]	[2.77]	[2.38]						
$FSIS\_OIB_t$				0.010**	0.007	0.004			
				[1.98]	[1.35]	[0.79]			
$FSIS\_ECS_t$							0.056***	0.044***	0.034***
							[9.12]	[6.64]	[4.54]
Constant	-1.203***	-1.201***	-1.274***	-1.367***	-1.346***	-1.409***	-1.387***	-1.360***	-1.407***
	[-11.54]	[-10.58]	[-9.45]	[-14.69]	[-14.34]	[-12.45]	[-12.32]	[-11.59]	[-10.36]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,740	11,428	9,422	13,163	10,864	8,955	14,104	11,596	9,516
Adjusted-R^2	0.282	0.277	0.278	0.334	0.323	0.320	0.311	0.297	0.291

Table 10. Extended sample period

This table reports the panel regressions of *TFP* on *FSIS* and control variables, using two extended sample periods. The sample period is 1992–2019 in columns (1)–(3) and 2002–2019 in columns (4)–(6). Columns (1) and (4) report the results of the baseline regressions in Table 2, where the dependent variable is TFP_t and the independent variables of interest are $FSIS\_OR_t$ and $FSIS\_ECS_t$. Columns (2) and (5) report the results of the regressions in Panel A of Table 6, where the dependent variable is ΔTFP_t and the independent variables of interest are $\Delta FSIS\_OR_t$ and $\Delta FSIS\_ECS_t$. Columns (3) and (6) report the results of the regressions in Panel B of Table 6, where the dependent variable is TFP_t and the independent variables of interest are $FSIS\_OR_{t-1}$ and $FSIS\_ECS_{t-1}$. All variables are defined in Appendix A. The coefficients of the control variables, Fama–French 48 industry fixed effects, and year fixed effects are suppressed for brevity in the respective columns. t-statistics based on standard errors clustered at the firm level are reported in brackets. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	TFP_t	ΔTFP_t	TFP_t	TFP_t	ΔTFP_t	TFP_t
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$FSIS\_OR_t$	0.008***					
	[3.39]					
$\Delta FSIS\_OR_t$		0.006***				
		[3.76]				
$FSIS\_OR_{t-1}$			0.006***			
			[2.89]			
$FSIS\_ECS_t$				0.073***		
				[16.89]		
$\Delta FSIS\_ECS_t$					0.039***	
					[17.16]	
$FSIS\_ECS_{t-1}$						0.048***
						[11.45]
Constant	-1.132***	0.017	-1.222***	-1.362***	-0.012	-1.441***
	[-15.45]	[1.04]	[-16.59]	[-17.38]	[-0.64]	[-18.21]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	55,972	46,134	48,580	29,911	25,000	25,639
Adjusted-R^2	0.269	0.157	0.305	0.324	0.185	0.337

Table 11. Firm-specific investor sentiment and operational efficiency

This table reports the panel regressions of firm operational efficiency on *FSIS* and control variables. The dependent variables are $Sale/Cost_t$ in columns (1)–(3), $Asset\_Turnover_t$ in columns (4)–(6), ROA_t in columns (7)–(9), and $Negative\_NI_t$ in columns (10)–(12). The independent variables of interest are $FSIS\_OR_t$, $FSIS\_OIB_t$, and $FSIS\_ECS_t$. The control variables are the same as those in Table 2. All variables are defined in Appendix A. The coefficients of the control variables, Fama–French 48 industry fixed effects, and year fixed effects are suppressed for brevity in the respective columns. t-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$Sale/Cost_t$			$Asset\_Turnover_t$			ROA_t			$Negative\_NI_t$		
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
$FSIS\_OR_t$	0.012***			0.034***			0.007***			-0.026***		
	[5.10]			[4.08]			[7.50]			[-6.63]		
$FSIS\_OIB_t$		0.009***			0.015*			0.003***			-0.011***	
		[4.23]			[1.73]			[3.64]			[-2.64]	
$FSIS\_ECS_t$			0.017***			0.024**			0.016***			-0.092***
			[5.98]			[2.23]			[15.14]			[-22.00]
Constant	0.856***	0.798***	0.769***	1.811***	1.884***	1.786***	0.047**	-0.009	-0.009	0.507***	0.768***	0.758***
	[18.12]	[19.73]	[17.29]	[9.97]	[12.49]	[11.94]	[2.34]	[-0.45]	[-0.44]	[7.36]	[10.23]	[10.93]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,206	14,835	15,786	12,841	12,090	12,890	12,841	12,090	12,890	15,206	14,835	15,786
Adjusted- or Pseudo R^2	0.370	0.414	0.383	0.454	0.427	0.455	0.340	0.359	0.364	0.165	0.200	0.232