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ABSTRACT

Using the implementation of the EDGAR system from 1993 to 1996 as a shock to information dissemination technologies, we examine the potential benefits and costs of modern information technologies on the real economy. On the one hand, we document that broader information dissemination leads to a decrease in the cost of capital and an increase in the level of equity financing and corporate investment. On the other hand, we provide evidence that greater dissemination of corporate disclosures crowds out investors' private information acquisition and reduces managerial learning from stock prices. Our findings suggest that it is important to consider this tradeoff between improved equity financing and reduced managerial learning when evaluating the economic effects of modern information technologies. Our evidence suggests that the former effect dominates in value firms while the latter effect dominates in high-growth firms.

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1. Introduction

One of the most important developments in financial markets over the years is the greater availability of information to various market participants. Much of the information originates from firms themselves, as disclosures are enhanced and information technologies for their dissemination improve. Aside from understanding the financial-market implications, a fundamental, perhaps more important, question is about the effects on the real economy (Goldstein and Yang 2017). After all, the main function of financial markets is to assure the efficient allocation of capital, either directly or through the signals market prices provide. Despite the large literature (Roychowdhury, Shroff, and Verdi 2019), there is still a lot that is unknown: theory generates different predictions with some tensions and nuances, and empirically, causal effects are difficult to infer in most settings. In this paper, we use a quasi-natural experiment, generated by the implementation of the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system in the United States, to address this important question. This setup allows us to examine how a shock to the dissemination of information from the firm to the market, brought by technological advances, affects corporate investment, and what the implications are for the efficiency of capital allocation and investment decisions.

Fundamentally, the enhancement of information dissemination from firms to the market allows investors, who otherwise would not have this information, to benefit from it. Following prior theoretical literature, we argue that this can have two types of effects on corporate investment. First, making corporate disclosures more easily available levels the playing field in the market and mitigates information asymmetry among investors. This can help firms broaden their investor base, attract liquidity to the secondary market, and eventually achieve a lower cost of capital in the primary market (Merton 1987; Diamond and Verrecchia 1991). Based on this argument, reduced costs of accessing firm disclosures should lead to an increased level of equity financing and corporate investment. To the extent that corporate filings disseminated by the EDAGR system likely contain more information about assets in place than that about growth options, we expect this equity-financing effect to be more evident in value firms than in growth firms.

Second, while the above channel touches on asymmetric information regarding firms' disclosures, it is also important to consider the implications that leveling the playing field in the financial market has for investors' incentives to acquire information that is not disclosed by firms and might not be otherwise known to firms. This will affect revelatory price efficiency (i.e., the extent to which prices reveal new information to managers) and corporate investment decisions (Bond, Edmans, and Goldstein 2012). Learning models commonly assume that investors' information advantage lies in evaluating growth options, which requires analyzing market trends, industry competition, and consumer demand, as well as making comparisons with other firms; investors are unlikely to possess new information about a firm's assets in place since managers observe first-hand information on these assets (e.g., Gao and Liang 2013; Bai, Philippon, and Savov 2016; Edmans, Jayaraman, and Schneemeier 2017; Goldstein and Yang 2019). It is worth noting that these models do not argue that the managers of growth firms are less informed than their investors but rather that the investors of growth firms are likely to possess more information that is new to managers than the investors of value firms.

This intuition can be best illustrated in Figure 1 (Zuo 2016). The direct effect of the EDGAR implementation is transferring managers' private information M into common information M'. Since the information disseminated by EDGAR mainly pertains to payoffs of assets in place, this direct effect is likely to be stronger in value firms (where M mainly concerns assets in place) than in growth firms (where M mainly concerns growth options). However, what matters to managerial learning is the amount of investors' information N that is incorporated into prices. Theories point to different effects of the EDGAR implementation on N and the resulting level of corporate investment. On the one hand, the fact that broader dissemination of corporate disclosures reduces uncertainty may encourage risk-averse traders to increase information acquisition and trading on information potentially unknown to managers, resulting in a crowding-in effect, i.e., an increase in N (Goldstein and Yang 2015). This increase in price informativeness can reduce the uncertainty about future fundamentals facing managers and lead to more investment. On the other hand, a decline in the cost of accessing corporate disclosures can reduce the equilibrium demand for more precise fundamental signals obtained with a deeper analysis, leading to a crowding-out effect, i.e., a decrease in N (Dugast and Foucault 2018).[1] This, in turn, can increase the uncertainty facing managers and lead to a reduction in investment. As learning models argue that N is likely to be larger for growth firms than for value firms,[2] we expect the effect of the EDGAR implementation on learning from prices, if any, to be stronger in growth firms.

To evaluate the real effects of modern information technologies, we exploit the staggered implementation of the EDGAR system from 1993 to 1996 as a shock to information dissemination technologies that alter the timeliness and costs of accessing firm disclosures (Gao and Huang 2020; Chang, Ljungqvist, and Tseng 2021). On February 23, 1993, the Securities and Exchange Commission (SEC) specified a phase-in schedule for registered firms to start filing on EDGAR in ten discrete groups (SEC Release No. 33-6977). Firms in the first and last groups became EDGAR

[1] This crowding-out effect happens because it takes time to develop high precision signals and the trading profits based on these signals are reduced when low precision signals have already been reflected in prices. This would affect the sophisticated traders, who had access to firms' disclosures prior to the dissemination shock and lost their informational advantage as a result.
[2] Aboody and Lev (2000) provide early evidence that insiders in R&D-intensive firms make more trading profits than insiders in firms without R&D. This evidence is consistent with the idea that M is also larger in growth firms than in value firms. It suggests that the opaqueness of R&D-intensive firms can incentivize outsiders to acquire private information that is not yet reflected in prices (i.e., either M or N).

filers in April 1993 and May 1996, respectively. This staggered mandatory implementation of the EDGAR system reduces potential endogeneity concerns caused by unobserved firm-, industry-, or market-level shocks or reverse causality (Leuz and Wysocki 2016). For an omitted variable to confound our findings, it needs to affect different groups of firms at discrete points in time as specified in the phase-in schedule.

Using a staggered difference-in-differences (diff-in-diff) research design, we find that the EDGAR implementation leads to a 10% increase in the level of corporate investment. This result continues to hold after we control for group-specific time trends or use a stacked diff-in-diff design (Cengiz, Dube, Lindner, and Zipperer 2019).[3] A standard dynamic test shows no difference in pre-trends in investment behavior between the treatment and control groups, supporting the parallel-trends assumption. These results confirm the hypothesis that leveling the playing field via information dissemination helps firms tap into new investment opportunities and invest more.

The increased level of investment after the EDGAR implementation can be driven by improved equity financing and/or enhanced managerial learning. Based on the theoretical discussions earlier, we expect the former effect to manifest in value firms while the latter effect, if any, to manifest in growth firms. We conduct a series of analyses to understand the underlying mechanisms. As a first step, we explore cross-sectional differences between firms and find that the investment effect is concentrated in value firms. This result suggests that the investment effect is likely driven by improved equity financing for value firms (rather than enhanced managerial learning for growth firms).

[3] The staggered diff-in-diff approach implicitly takes as the control group both already-treated firms and to-be-treated firms (Bertrand and Mullainathan 2003). The stacked diff-in-diff approach restricts the control group to the set of to-be-treated firms.

To provide more direct evidence on the equity financing channel, we examine the treatment effect of the EDGAR shock on a firm's implied cost of capital (Gebhardt, Lee, and Swaminathan 2001; Lee, So, and Wang 2021) and equity issuance. We show that, after a firm becomes an EDGAR filer, the firm indeed faces a lower cost of equity capital and obtains more equity financing; and these effects are again concentrated in value firms than in growth firms. These findings are consistent with our prediction that EDGAR inclusion improves a firm's information environments and access to equity capital, and that this is the primary channel behind its ability to undertake more investments.

While the increased level of investment is unlikely to be explained by enhanced managerial learning, we perform various tests to understand whether and how the EDGAR implementation affects revelatory price efficiency. First, we find that the EDGAR implementation leads to a 20% decrease in the investment-to-price sensitivity, suggesting that there is a crowding-out effect acting to reduce the ability of firms to use new information in prices as guidance for their investment decisions. Second, we show that, after a firm becomes an EDGAR filer, it experiences a decrease in ownership by institutional investors, especially those who are more likely to actively acquire and trade on information. This result suggests that the EDGAR implementation provides greater benefits to less-sophisticated retail investors and discourages private information acquisition by more-sophisticated institutional investors. Third, we use two measures based on structural market microstructure models to assess the equilibrium level of private information in prices (Armstrong, Core, Taylor, and Verrecchia 2011; Duarte, Hu, and Young 2020), and we show that the EDGAR implementation leads to a decrease in both measures of private information. In addition, we find that growth firms experience a greater reduction in the investment-to-price sensitivity, institutional ownership, and privately informed trading after the EDGAR shock than value firms.

As a final step, we examine the overall effect of the EDGAR implementation on *ex post* firm performance. On the one hand, greater dissemination of corporate disclosures can better incentivize managers (who are the agents of the shareholders) to take value-maximizing actions. On the other hand, reduced managerial learning, especially in growth firms, can hurt firm performance (despite managers' best intentions). Empirically, we find that, on average, the EDGAR implementation leads to an increase in firm profitability and sales growth in value firms but hurts performance in high-growth firms where managerial learning from the market is particularly important.

It is worth noting that the increased timeliness and reduced costs of accessing firm disclosures might alter managers' reporting incentives (by enhancing investor monitoring and/or increasing capital market pressure) and affect firms' disclosure quality. Thus, the EDGAR shock may represent changes to information dissemination and disclosure quality at the same time. This possibility adds nuance to the interpretation of our results but does not change our inferences that the documented real effects of the EDGAR shock are due to a reduction in investors' costs of accessing corporate filings.

The remainder of the paper is organized as follows. Section 2 reviews related literature and discusses our paper's contributions. Section 3 lays out the institutional setting and describes our sample and empirical specification. Section 4 presents the main analysis on corporate investment. Sections 5 and 6 delve into the underlying mechanisms that explain the main results. Section 7 presents the analysis on firm performance. Section 8 concludes and discusses some directions for future research.

2. Related Literature

Modern information technologies have fundamentally changed the way that the investing public monitors, acquires, and analyzes firm disclosures. A natural question that arises is whether and how these technologies affect capital markets and firms. Gao and Huang (2020) first exploit the staggered timing of the EDGAR implementation and provide plausibly causal evidence that EDGAR inclusion leads to an increase in information production by individual investors and sell-side analysts, and a higher stock pricing efficiency.[4] Their results are based on the amount of total information in individual trades, analyst forecasts, and prices, and suggest that the EDGAR implementation improves forecasting price efficiency (i.e., the extent to which prices reflect all available information). We follow the empirical methodology of Gao and Huang (2020), highlight the opposite effects of EDGAR inclusion on the two types of price efficiency (i.e., forecasting price efficiency versus revelatory price efficiency), and demonstrate the different effects of modern information technologies on value firms and growth firms.

Our results show that broader information dissemination leads to a decrease in the cost of equity capital and an increase in the level of equity financing and corporate investment. In addition, we provide evidence that greater dissemination of corporate disclosures crowds out investors' private information acquisition and reduces managerial learning from prices. This crowding-out effect is particularly pronounced in high-growth firms. Overall, our findings provide evidence that investors' costs of accessing firm disclosures have important implications for the real economy.

As evidence of the importance of this line of research, several concurrent studies also exploit the staggered timing of the EDGAR implementation.[5] Most related to our work is Bird,

[4] Earlier studies treat the implementation of the EDGAR system as a one-time shock (e.g., Asthana, Balsam, and Sankaraguruswamy 2004).

[5] These studies examine various outcome variables, including investor disagreement (Chang, Hsiao, Ljungqvist, and Tseng 2021), analyst forecasts (Chang, Ljungqvist, and Tseng 2021), stock price crash risk (Guo, Lisic, Stuart, and

Karolyi, Ruchti, and Truong (2021) who focus on one result in our paper – the investment-to-price sensitivity.[6] Our paper provides a more comprehensive picture of the relations at play by considering both types of price efficiency and by assessing whether and when the benefits exceed the costs and vice versa. Our findings highlight that it is important to consider the tradeoff between improved equity financing and reduced managerial learning when evaluating the economic effects of modern information technologies. Our evidence suggests that the former effect dominates in value firms while the latter effect dominates in high-growth firms.

Our paper makes contributions to two strands of literature. First, it contributes to the literature on the effects of financial reporting and disclosure on corporate investment (see reviews in Kanodia and Sapra (2016), Leuz and Wysocki (2016), and Roychowdhury, Shroff, and Verdi (2019)). Exploiting the staggered mandatory implementation of the EDGAR system, we show that information technologies affect corporate investment and that they do so causally. In addition, our findings highlight the importance of considering information dissemination beyond information production when examining the real effects of corporate disclosures.[7]

Second, our paper contributes to the literature assessing how the costs of monitoring, acquiring, and analyzing corporate disclosures affect investor information choices, trades, and market outcomes (see reviews in Lee and So (2015), Kothari, So, and Verdi (2016), and Blankespoor, deHaan, and Marinovic (2020)). In this literature, two financial reporting

Wang 2019; Ni, Wang, and Yin 2021), information asymmetry (Gomez 2020), cost of capital (Lai, Lin, and Ma 2020), corporate tax avoidance (Chen, Hong, Kim, and Ryou 2021), and financial reporting (Liu 2021).

[6] Bird, Karolyi, Ruchti, and Truong (2021) do not examine the benefits of modern information technologies or assess whether and when the benefits exceed the costs and vice versa. Specifically, they do not analyze the level of corporate investment or the equity financing channel. For the managerial learning channel, they do not provide evidence on how EDGAR affects investor clientele, privately informed trading, or firm performance. They do not consider the heterogeneous effects between value firms and growth firms either.

[7] Prior research in this literature often assumes that investors' costs of acquiring and analyzing corporate disclosures are negligible and focuses on whether and how disclosure content, quantity, quality, or timing affects managerial actions.

technologies have attracted the most academic attention, i.e., the SEC's EDGAR system and the eXtensible Business Reporting Language (XBRL). While evidence suggests that the XBRL mandate seems to have initially disadvantaged retail investors and unleveled the playing field (Blankespoor, Miller, and White 2014; Li, Zhu, and Zuo 2021), the EDGAR implementation benefited retail investors (Gao and Huang 2020). We provide further evidence suggesting that the EDGAR implementation decreases the amount of information in prices that is new to managers (i.e., revelatory price efficiency) despite its positive effect on forecasting price efficiency.

3. Institutional Setting, Sample, and Empirical Specification

3.1. Institutional Setting

Before the implementation of the EDGAR system in 1993, SEC-registered firms were required to submit multiple paper copies of filings to the SEC. These paper copies of filings were stored in the SEC's public reference rooms located in three locations (i.e., Washington D.C., New York, and Chicago), and typically one or two paper copies of the same filing were available for access in each location. As vividly noted in a *New York Times* (1982) article, "[t]he place can be a zoo" and "files are often misplaced or even stolen."[8] To view these corporate filings, investors could either physically visit one of the reference rooms or subscribe to commercial data vendors for a nontrivial fee.[9] Data aggregators such as Standard & Poor's were only able to disseminate SEC filings to its commercial customers with a significant production lag (D'Souza, Ramesh, and

[8] See "S.E.C. Data: Difficult Hunt" by the *New York Times* (May 19, 1982).
[9] Chang, Ljungqvist, and Tseng (2021, p. 6) note that Mead Data Central charged "a fee of $125 per month, plus a connect charge of $39 an hour, plus a charge of 2.5 cents per line of data plus search charges which range from $6 to $51 per search." Dialog charged "$84 per hour plus $1 per page." See http://www.bio.net/bionet/mm/ag-forst/1992-January/000187.html.

Shen 2010).[10] This restricted and delayed access to firm disclosures likely creates information asymmetry among investors even though these SEC filings are deemed to be "public."[11]

To facilitate the timely dissemination of corporate filings through the internet, the SEC developed the EDGAR system which enabled registered firms to file electronically. On February 23, 1993, the SEC released the phase-in schedule for the mandatory implementation of the EDGAR system (SEC Release No. 33-6977). In this schedule, all SEC-registered firms were divided into ten groups, and each group was required to submit corporate filings (e.g., 10-K, 10-Q, and 8-K) electronically through the EDGAR system after the respective implementation date.[12] The assignments of firms into the ten phase-in groups were solely based on firm size, where larger firms were required to start filing electronically earlier than smaller firms (SEC Release No. 33-6944).[13] According to the schedule, firms in the first group (i.e., Group CF-01) were required to start filing through the EDGAR system in April 1993, while firms in the last group (i.e., Group CF-10) were required to do so in May 1996.[14] The detailed implementation dates for the ten groups are tabulated in Appendix A.

[10] D'Souza, Ramesh, and Shen (2010) show that EDGAR decreased the Compustat's median collection lag by 50 percent (i.e., from 22 weekdays to 11 weekdays).

[11] Griffin (2003) and Li and Ramesh (2009) document significant stock price reactions surrounding 10-K and 10-Q filings in the EDGAR era.

[12] Initially, filers were not required to submit electronically their Forms 3, 4 and 5 (reporting insider ownership or trading). Effective June 30, 2003, filers became required to do so (SEC Release No. 33-8230).

[13] Chang, Ljungqvist, and Tseng (2021, p. 2) note: "In private correspondence, Scott Bauguess, then Acting Chief Economist of the SEC, informed us that the wave assignments were determined solely on the basis of firm size." Gao and Huang (2020) further note that very few firms (3% of sample firms) deviated from the SEC's phase-in schedule. Thus, the prespecified timing is a strong instrument for the actual timing of the EDGAR implementation and has the advantage of not being contaminated by firms' endogenous decisions.

[14] After completing the phase-in of the first four groups in December 1993, the SEC refrained from further phase-in of EDGAR filers over the first half of 1994 while evaluating EDGAR's performance. On December 19, 1994, the SEC issued Release No. 33-7122, which revised the phase-in dates for Group CF-05 and Group CF-06 (from August and November 1994 as in Release No. 33-6977 to January and March 1995, respectively) and confirmed the phase-in dates for the remaining four groups. Our analysis is based on the finalized implementation dates.

3.2.Sample

To construct the sample for our analysis, we obtain the list of firms in these ten groups from the SEC Release No. 33-6977. This list contains each firm's Central Index Key (CIK), which we use to match these firms to Compustat. Our sample period starts in the second quarter of 1991 (i.e., two years before the implementation date of the first phase-in group) and ends in the second quarter of 1998 (i.e., two years after the implementation date of the last phase-in group). We obtain financial statement data from Compustat, stock price and return data from the Center for Research in Security Prices (CRSP), analyst forecast data from IBES, intraday transaction data from NYSE Trade and Quote (TAQ), and data on institutional ownership from Thomson Reuters. Following prior research (e.g., Chen, Goldstein, and Jiang 2007), we exclude firms in the financial and utility industries as well as firms with total assets less than $10 million in 1992 (i.e., the last year prior to the EDGAR implementation). Our final sample consists of 3,020 firms and 66,628 firm-quarter observations.

3.3.Empirical Specification

Our baseline equation for testing the effect of the EDGAR implementation on the level of corporate investment is as follows:

$$INVESTMENT_{i,t+1} = \alpha_t + \eta_i + \gamma_1 EDGAR_{i,t} + \gamma_2 Q_{i,t} + \gamma_3 CF_{i,t} + \gamma_4 SIZE_{i,t} + \varepsilon_{i,t+1} \quad (1)$$

where $INVESTMENT_{i,t+1}$ is firm *i*'s investment in quarter *t*+1, and α_t and η_i represent year-quarter and firm fixed effects, respectively. Specifically, $INVESTMENT_{i,t+1}$ is defined as firm *i*'s capital expenditure in quarter *t*+1 scaled by its net property, plant, and equipment at the end of quarter *t*. $EDGAR_{i,t}$ is an indicator variable that equals one if firm *i* is a mandatory EDGAR filer in quarter *t*, and zero otherwise. Following prior research (Foucault and Frésard 2012, 2014), we control for three variables known to correlate with a firm's investment decisions: $Q_{i,t}$ is Tobin's

Q of firm i measured at the end of quarter t. $CF_{i,t}$ is the operating cash flow of firm i in quarter t, scaled by lagged book assets. $SIZE_{i,t}$ is the natural logarithm of the book value of total assets of firm i measured at the end of quarter t.[15]

γ_1 is the diff-in-diff estimator that captures the effect of the EDGAR implementation on the level of corporate investment. We predict that the EDGAR implementation improves firms' information environments, facilitates firms' access to equity financing, and allows them to tap into new investment opportunities. Thus, we predict a positive γ_1.

Two things are worth noting. First, the assignments of firms into the ten phase-in groups were solely based on a snapshot of pre-EDGAR market capitalization (Chang, Ljungqvist, and Tseng 2021). Equation (1) does not include a control for pre-EDGAR market capitalization because it is subsumed by firm fixed effects. Second, the time-varying firm characteristics (i.e., $Q_{i,t}$, $CF_{i,t}$, and $SIZE_{i,t}$) are likely affected by the EDGAR implementation and controlling for them might confound the estimate of the effect of the EDGAR implementation on investment (Angrist and Pischke 2009; Gao and Huang 2020).[16] Hence, we run all our regressions without and with controlling for time-varying firm characteristics, and the specification without these endogenous controls is our preferred one. We cluster standard errors by firm given multiple quarterly observations for each firm (Petersen 2009).

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[15] Our inferences are unchanged when we use the natural logarithm of the market capitalization at the end of quarter t to proxy for firm size (see Table A1 of the online appendix).

[16] Gormley and Matsa (2016) illustrate the importance of excluding endogenous controls (e.g., firm size) when examining the effects of business combination (BC) laws. They note: "For example, prior studies of how BC laws affect firms' acquisition activity have included a time-varying control for firm size. But, presumably, if passage of the BC law affects acquisitions, it also affects firm size, making firm size an invalid control" (p. 443).

4. Main Analysis

4.1.Descriptive Statistics

Table 1 reports the descriptive statistics for the variables used in our main analysis. All continuous variables are winsorized at the top and bottom one percent to mitigate the influence of extreme values. *INVESTMENT* exhibits reasonable variations in the sample; and its mean, median, and standard deviation are 7.1%, 4.9%, and 7.6%, respectively. We have a roughly equal number of firm-quarter observations before and after the EDGAR implementation (50.6% versus 49.4%). The average and median Tobin's Q are 1.8 and 1.4, respectively.

4.2.Main Results on Corporate Investment

We analyze the effect of the EDGAR implementation on corporate investment by estimating Equation (1). Panel A of Table 2 reports the baseline results. In column 1, we only include *EDGAR* as the independent variable, along with firm and year-quarter fixed effects. The coefficient on *EDGAR* is 0.613 (p-value<0.01), which represents a 9% increase relative to the sample mean of *INVESTMENT*. In column 2, we control for Tobin's Q (*Q*), cash flows (*CF*), and firm size (*SIZE*), and the coefficient on *EDGAR* remains significantly positive (p-value<0.01). These results suggest that, on average, the EDGAR implementation leads to an increase in the level of corporate investment.

As noted earlier, the assignments of firms into the ten EDGAR phase-in groups were based on firm size. To ensure that our results are not confounded by time trends that vary across different sizes of firms, we control for group-specific time trends. Panel B of Table 2 shows that both the coefficient on *EDGAR* and the adjusted R-squared remain quite similar to those reported in Panel A. These results provide comfort that group-specific time trends do not seem to explain the time-series variation in corporate investment or confound our estimation of the EDGAR effect.

The staggered diff-in-diff approach above implicitly takes as the control group both already-treated firms and to-be-treated firms (Bertrand and Mullainathan 2003). Recent research demonstrates that this approach can produce biased estimates in the presence of delayed or heterogeneous treatment effects (e.g., Baker, Larcker, and Wang 2021; Barrios 2021). To ensure the robustness of our results, we use a stacked diff-in-diff approach in which the control group is restricted to the set of to-be-treated firms (Cengiz, Dube, Lindner, and Zipperer 2019). To conduct this analysis, we construct a matched sample where treated firms are from groups CF-01 through CF-07 and control firms are selected from the set of to-be-treated firms using a nearest-neighbor propensity-score method.[17] Treated firms are tracked in the window of event quarters [-4, +4], with quarter 0 being the EDGAR implementation quarter. We match treated and control firms on three dimensions (i.e., *Q*, *CF*, and *SIZE*) in the quarter before the EDGAR implementation and produce a stacked dataset that consists of seven groups of treated and control firms.[18] We include group-specific firm and year-quarter fixed effects in a stacked diff-in-diff analysis. Panel C of Table 2 shows that our results continue to hold in this specification.[19]

4.3. Parallel Trends

One important identifying assumption for the diff-in-diff estimates is that the treatment and control groups follow parallel trends in the absence of the EDGAR treatment.[20] A common way to assess the plausibility of this parallel-trends assumption is to check whether the treatment and control groups share similar trends prior to the treatment. Following Foucault and Frésard (2012),

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[17] Following Chang, Ljungqvist, and Tseng (2021), we exclude firms from groups CF-08 through CF-10 in constructing the treated firms as they lack (to-be-treated) control firms.

[18] We only consider matches in the common support, using a 0.05 caliper.

[19] A caveat with this stacked diff-in-diff analysis is that its reliance on propensity score matching can potentially produce unstable results (Angrist and Pischke 2009).

[20] The diff-in-diff approach does not require *ex ante* firm characteristics (e.g., firm size) to be identical between the treatment and control groups as any systematic difference between them will be eliminated in the estimation (through firm fixed effects).

we plot the dynamic diff-in-diff estimates (along with the 95% confidence intervals) of the effect of the EDGAR implementation on the investment level. Figure 2 shows that the level of investment is not statistically different between the treatment and control groups in the four quarters before the EDGAR implementation. These estimates provide support for the parallel-trends assumption. Moreover, Figure 2 shows that the treatment effect is rather persistent and does not exhibit any reversal in the quarters after the EDGAR shock.

4.4.Robustness Checks

We conduct two additional analyses to ensure the robustness of our results. First, we repeat our analysis after excluding firms assigned to Group CF-01 (i.e., the first group) as this group contains "transitional" filers that volunteered to file electronically prior to the mandatory phase-in of the EDGAR system in April 1993 (SEC Release No. 33-6977).[21] Table A2 of the online appendix reports the results for this analysis. Both the magnitude and statistical significance of the coefficient on *EDGAR* are quite similar to those reported in Table 2.

Second, we repeat our analysis after redefining the *EDGAR* indicator for firms assigned to groups CF-01 through CF-04 (i.e., the first four groups) to take the value of one if the firm-quarter is after January 17, 1994 (when all electronic EDGAR filings became freely available online via a National Science Foundation grant to New York University) and zero otherwise. Prior to January 17, 1994, electronic EDGAR filings were available through Mead Data Central (a commercial data vendor) for a fee.[22] Table A3 of the online appendix presents the results and our inferences remain largely unchanged.

[21] The SEC started developing an electronic disclosure system in 1983. A pilot system was opened for volunteers filing with the SEC by the fall of 1984. On July 15, 1992, the operational EDGAR system was made available to those filers. See the regulatory overview of electronic filing at: https://www.sec.gov/info/edgar/regoverview.htm.
[22] See "Plan Opens More Data to Public" by the *New York Times* (October 22, 1993).

4.5. Value Firms versus Growth Firms

The increased level of investment documented in Table 2 can result from improved equity financing and/or enhanced managerial learning after the EDGAR implementation, where the former effect is more likely to manifest in value firms while the latter effect, if any, is more likely to manifest in growth firms. To examine this cross-sectional difference between firms, we divide the full sample into these two types of firms based on the market-to-book ratios in 1992 (i.e., the last year prior to the EDGAR implementation). *VALUE_FIRM* (*GROWTH_FIRM*) is an indicator that equals one if a firm's market-to-book ratio in 1992 is below (above) the median, and zero otherwise.

In Panel A of Table 3, we repeat the analysis on the level of investment by replacing *EDGAR* in Equation (1) with its interactions with *VALUE_FIRM* and *GROWTH_FIRM*. We find that the observed EDGAR effect on corporate investment is concentrated in value firms. To ensure that this result based on the value and growth dichotomy is not confounded by the propensity to treat (based on firm size), we further control for *EDGAR×PRE_MVE* in Panel B of Table 3, where *PRE_MVE* is the pre-EDGAR market capitalization (measured in 1992). We continue to observe a significantly positive coefficient on *EDGAR×VALUE_FIRM*, while both the coefficient on *EDGAR×GROWTH_FIRM* and that on *EDGAR×PRE_MVE* are small and statistically insignificant. These results suggest that the investment effect is likely driven by improved equity financing for value firms (rather than enhanced managerial learning for growth firms).

To provide further evidence on the underlying mechanisms, we more directly examine the equity financing channel and the managerial learning channel in the next two sections.

5. Equity Financing Channel

In this section, we analyze the equity financing channel through which the EDGAR implementation affects the level of corporate investment by estimating the following model:

$$DEPVAR_{i,t} = \alpha_t + \eta_i + \beta_1 EDGAR_{i,t} + \beta_2 SIZE_{i,t-1} + \beta_3 PRC\_INV_{i,t-1} + \varepsilon_{i,t} \quad (2)$$

where $DEPVAR_{i,t}$ represents the implied cost of capital (*ICC*) measure derived from Gebhardt, Lee, and Swaminathan (2001) and the amount of equity issuance (*EQUITY*). Gebhardt, Lee, and Swaminathan (2001) use a residual-income model to compute a firm's implied cost of capital, defined as the internal rate of return that equates the firm's market value to the present value of its expected future earnings estimates (from analysts' forecasts). This measure is well suited in our setting as our objective is to compare the difference in a firm's cost of capital over time (Lee, So, and Wang 2021).[23]

Following Jayaraman and Wu (2019), we include two basic controls. $SIZE_{i,t-1}$ is the lagged firm size (the natural logarithm of total assets), and $PRC\_INV_{i,t-1}$ is the inverse of stock price measured at the end of quarter *t*–1. Year-quarter fixed effects (α_t) and firm fixed effects (η_i) are included. We run our regressions without and with controlling for time-varying firm characteristics, and the specification without these endogenous controls is our preferred one.

Panel A of Table 4 reports the regression results. We include only *EDGAR* as the independent variable in columns 1 and 3 and add firm size (*SIZE*) and the inverse of stock price (*PRC_INV*) as controls in columns 2 and 4. In columns 1 and 2, the coefficient on *EDGAR* is significantly negative at the 5% level, suggesting a decrease in a firm's cost of equity capital by

[23] Lee, So, and Wang (2021) thoroughly evaluate alternative proxies of cost of capital and demonstrate that "implied-costs-of-capital" metrics perform best in time series (while "characteristic-based" proxies perform best in the cross-section). By comparing average cross-sectional measurement-error variances, they also show that the measure proposed by Gebhardt, Lee, and Swaminathan (2001) outperforms a trivial expected-return proxy.

0.195 percentage points after the EDGAR shock.[24] In columns 3 and 4, the dependent variable is the amount of equity financing (*EQUITY*). The coefficient on *EDGAR* is significantly positive (*p*-value<0.01) in both columns. The magnitude is also economically meaningful. The coefficient of 0.294 in column 3 suggests an increase in equity financing by 0.294% of total assets each quarter on average.

In Panel B of Table 4, we repeat the analysis on the equity financing channel by replacing *EDGAR* in Equation (2) with its interactions with *VALUE_FIRM* and *GROWTH_FIRM*. We find that the observed EDGAR effects on the implied cost of capital and corporate investment are concentrated in value firms. These results are consistent with the Myers and Majluf (1984) framework in which information asymmetry about assets in place (not growth options) causes adverse selection problems.

Collectively, Table 4 provides evidence supporting the equity financing channel: the EDGAR shock leads to a decrease in the implied cost of capital and an increase in equity financing, and these effects are concentrated in value firms.[25]

Our previous analysis focuses on the effect of EDGAR inclusion on equity financing instead of debt financing because the former is more likely to be negatively affected by information asymmetry (Myers and Majluf 1984; Kim, Li, Pan, and Zuo 2013). Even though the EDGAR implementation reduces the information asymmetry between firms and investors, firms are still likely to follow the pecking order of financing, i.e., using internal funds first, then issuing debt, and lastly raising equity. Thus, the observed increase in equity financing after the EDGAR

[24] Lai, Lin, and Ma (2020) also examine the effect of the EDGAR shock on a firm's cost of capital and provide similar findings. However, they do not analyze how the EDGAR shock affects a firm's investment, which is the focus of our paper.
[25] We also find consistent evidence that the EDGAR shock leads to an increase in stock market liquidity, measured by the simple bid-ask spread and the high-low spread estimator (Corwin and Schultz 2012), and this liquidity effect shows up in both value firms and growth firms (see Table A4 of the online appendix).

implementation is unlikely to reflect a substitution of equity for debt. Consistent with this prediction, we find no evidence that the EDGAR implementation affects the amount of debt financing (see Table A5 of the online appendix).

6. Managerial Learning Channel

In the previous section, we show that the EDGAR implementation affects the level of corporate investment through the equity financing channel, which is concentrated in value firms. In this section, we complete the picture by investigating whether and how the EDGAR implementation affects revelatory price efficiency, which is expected to be concentrated in growth firms.

6.1. Investment-to-Price Sensitivity

The notion of revelatory price efficiency builds on the idea that prices are a useful source of new information (Hayek 1945).[26] Stock prices can reveal dimensions of traders' private information which are new to managers, and hence they can affect managers' forecasts about their own firms' fundamentals (Zuo 2016; Jayaraman and Wu 2020) and their corporate investment decisions (Dye and Sridhar 2002; Luo 2005; Chen, Goldstein, and Jiang 2007).[27]

[26] Fama and Miller (1972, p. 335) note: "(An efficient market) has a very desirable feature. In particular, at any point in time market prices of securities provide accurate signals for resource allocation; that is, firms can make production-investment decisions …" Rappaport (1987, p. 57) further note: "(Managers) can learn a lot if they analyze what the stock price tells them about the market's expectations for their company's performance." George Soros (a prominent trader) calls this feature "reflexivity" and state: "Stock prices are not merely passive reflections; they are active ingredients in the process in which both stock prices and the fortunes of companies whose stocks are traded are determined" (Soros 1994, p. 49).

[27] As a recent anecdote of managerial learning from the market, Intercontinental Exchange (ICE, the parent company of the New York Stock Exchange) quickly abandoned its pursuit of eBay after the news of its interest in a deal triggered a 10.5% drop in its stock price. See "NYSE Owner Abandons Potential eBay Deal" by the *Wall Street Journal* (February 6, 2020). Goldstein, Liu, and Yang (2021) provide survey evidence that 90% of firms in China report that they pay attention to the stock market for learning and financing purposes. Zhang (2021) provides evidence that managers learn from their firms' institutional investors through direct interactions.

Measuring revelatory price efficiency directly is hard. An indirect proxy that emerged from prior literature is based on the investment-to-price sensitivity.[28] The intuition is that the sensitivity of investment to price will be stronger when movements in the price are more likely to originate from information that is new to the manager than from information that was already known to her.[29] We develop a stylized model in Appendix B to illustrate the basic mechanism underlying this general prediction.

To examine how the EDGAR implementation affects the investment-to-price sensitivity, we augment Equation (1) by interacting $EDGAR_{i,t}$ with $Q_{i,t}$, $CF_{i,t}$, and $SIZE_{i,t}$ as follows:

$$\begin{aligned} INVESTMENT_{i,t+1} &= \alpha_t + \eta_i + \gamma_1 EDGAR_{i,t} + \gamma_2 Q_{i,t} + \gamma_3 CF_{i,t} + \gamma_4 SIZE_{i,t} + \gamma_5 Q_{i,t} \times EDGAR_{i,t} \\ &+ \gamma_6 CF_{i,t} \times EDGAR_{i,t} + \gamma_7 SIZE_{i,t} \times EDGAR_{i,t} + \varepsilon_{i,t+1} \end{aligned} \quad (3)$$

where γ_5 captures the effect of the EDGAR implementation on the investment-to-price sensitivity. We do not have a signed prediction for γ_5 because it depends on how the EDGAR implementation affects revelatory price efficiency, which is *ex ante* unclear.

Table 5 presents the results of the analysis on the managerial learning channel. In column 1 of Panel A, we report the results of the regression model in Equation (3). The coefficient on *Q* measures the investment-to-price sensitivity prior to the EDGAR implementation and is 1.908 (*p*-value<0.01). The coefficient on *Q*×*EDGAR* measures the change in the sensitivity of investment to price after the EDGAR shock and is -0.392 (*p*-value<0.01). Comparing these two coefficients suggests that the EDGAR implementation leads to a 21% decline in the investment-to-price sensitivity.

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[28] See, for example, Chen, Goldstein, and Jiang (2007), Bakke and Whited (2010), Foucault and Frésard (2012, 2014), Bai, Philippon, and Savov (2016), Edmans, Jayaraman, and Schneemeier (2017), Dessaint, Foucault, Frésard, and Matray (2019), Jayaraman and Wu (2019), and Lin, Liu, and Sun (2019).

[29] While revelatory price efficiency is necessary for managerial learning, it is not sufficient. The extent to which managers incorporate price information in their decision making depends on their willingness and ability to learn, which is ultimately an empirical question (Hanlon, Yeung, and Zuo 2022).

In column 2 of Panel A, we further augment Equation (3) by interacting *Q* with firm fixed effects to allow the investment-to-price sensitivity to vary across firms. The coefficient on *Q×EDGAR* remains significantly negative (*p*-value<0.05).[30] In column 3 of Panel A, we use the same stacked diff-in-diff approach as in Panel C of Table 2 and continue to find a significantly negative coefficient on *Q×EDGAR*.

These results in Panel A suggests that EDGAR inclusion leads to a crowding-out effect and reduces managerial learning from prices. This observed decrease in the investment-to-price sensitivity is unlikely to be explained by alternative channels, such as greater financing, stronger governance or less noise in prices after the EDAGR implementation (e.g., Kanodia and Lee 1998; Bushee and Friedman 2016), which all point to an increase in the investment-to-price sensitivity. Interestingly, the coefficients on *CF* and *CF×EDGAR* are both significantly positive. Since a firm's cash flows are informative about its performance and investment opportunities (Alti 2003; Heitzman and Huang 2019), these results suggest that managers increase their reliance on internal profit signals (i.e., *CF*) and decrease their reliance on external price signals (i.e., *Q*) after the EDGAR implementation.

To provide further evidence to support the managerial learning channel, we perform a cross-sectional analysis. To the extent that investors' information advantage lies in evaluating growth options, we expect that EDGAR inclusion is likely to reduce managerial learning to a greater extent in growth firms than in value firms. In Panel B of Table 5, we repeat the regression on the investment-to-price sensitivity as specified in Equation (3) by replacing *Q* with *Q×VALUE_FIRM* and *Q×GROWTH_FIRM* in column 1, and we further add their interactions

[30] A caveat is that our result on the investment-to-price sensitivity is not robust after controlling for *Q* interacted with firm-specific time trends and/or year-quarter fixed effects. This might reflect an estimation issue when including many interaction terms that involve high-dimensional fixed effects.

with *EDGAR* in column 2. In column 1, the coefficients on both *Q×VALUE_FIRM* and *Q×GROWTH_FIRM* are significantly positive at the 1% level. In column 2, the interaction term *Q×GROWTH_FIRM×EDGAR* is significantly negative at the 1% level, while the coefficient on *Q×VALUE_FIRM×EDGAR* is statistically insignificant. Thus, the observed decline in the investment-to-price sensitivity after the EDGAR shock is concentrated in growth firms, in which managerial learning is expected to be more important.

6.2.Institutional Ownership

Gao and Huang (2020) find that trades by retail investors, especially those with access to the internet, become more informative about future stock returns after the EDGAR implementation. This result suggests that retail investors extract useful information from EDGAR filings for their trading purpose. However, we do not expect this information to be new to managers. Further, the EDGAR implementation likely provides greater benefits to retail investors who often lack the resources and skills to acquire information than to institutional investors. Thus, we expect a decline in a firm's institutional ownership (as a percentage of total shares outstanding) after the firm is included in the EDGAR system.

In Panel A of Table 6, we analyze the effect of the EDGAR shock on institutional ownership. The coefficient on *EDGAR* in column 1 is significantly negative at the 5% level and translates into a reduction of 0.72 percentage points in institutional ownership (*INSTOWN*). This result is consistent with our expectation that a firm's inclusion into the EDGAR system reduces the information advantage of some institutional investors and makes its stock relatively more attractive to retail investors.

Not all institutional investors actively trade on information. Prior research on informed trading commonly uses the institutional investor classification developed by Bushee (1998) and focuses on transient institutional investors (who hold small stakes in many firms and trade frequently in and out of stocks) as privately-informed investors (e.g., Ke and Petroni 2004; Ke and Ramalingegowda 2005; Akins, Ng and Verdi 2012). Thus, in columns 3 and 4, we analyze the effect of the EDGAR shock on transient institutional ownership (*INSTOWN_TRA*). The coefficient on *EDGAR* in column 3 is significantly negative at the 5% level and translates into a reduction of 0.38 percentage points in transient institutional ownership.

In addition, we repeat the regression for the other two types of institutional investors: quasi-indexers (who use indexing or buy-and-hold strategies characterized by high diversification and low portfolio turnover) and dedicated institutional investors (who have large, long-term holdings concentrated in only a few firms). These two types of institutional investors do not actively trade on information as transient institutional investors do, and they are unlikely to affect the extent of revelatory price efficiency. In Table A6 of the online appendix, we show that EDGAR inclusion leads to a decrease in quasi-indexer ownership but an increase in dedicated institutional ownership. The reduced ownership by quasi-indexers is consistent with the idea that EDGAR benefits retail investors more and leads to a disproportionate increase in retail investor ownership. The increased ownership by dedicated institutional investors suggests that EDGAR inclusion potentially reduces monitoring costs to these investors and leads to an increased demand from them.[31]

Together, the results in Panel A of Table 6 and Gao and Huang (2020) suggest that a firm's inclusion into the EDGAR system levels the playing field and makes its stock relatively more attractive to retail investors than to institutional investors who tend to actively trade on information. By making a firm's disclosures more readily available to retail investors, the EDGAR system

[31] Increased monitoring by investors post EDGAR is likely to lead to an increase in the investment-to-price sensitivity. The observed decrease in the investment-to-price sensitivity suggests that this net effect is likely driven by reduced managerial learning (instead of increased investor monitoring).

improves retail investors' information production but potentially discourages institutional investors' private information acquisition. To assess the equilibrium level of private information in prices, we rely on two measures based on structural market microstructure models in the next subsection.

6.3.Privately Informed Trading

We use two measures of private information based on structural market microstructure models. While there are no direct measures of revelatory price efficiency, these two measures of private information are likely to be positively correlated with the extent of revelatory price efficiency (Bond, Edmans, and Goldstein 2012). Our first measure is the probability of informed trading (*GPIN*) based on the Generalized PIN model recently developed in Duarte, Hu, and Young (2020). In the traditional PIN model (Easley, Kiefer, O'Hara, and Paperman 1996), private-information arrival is the only cause for increase in expected daily turnover. The GPIN model extends the PIN model by allowing expected daily turnover from noise trading to be random. Duarte, Hu, and Young (2020) show that the GPIN model matches the variability of noise trade in the data and identifies private-information arrival much better than other variants of the PIN model.

Our second measure is the adverse selection component of the bid-ask spread (*LAMBDA*). It represents the magnitude of the revision in the market-maker's beliefs concerning the stock's value induced by order flows, and is estimated as the extent to which stock prices are affected by unexpected order flows (Madhavan, Richardson, and Roomans 1997; Armstrong, Core, Taylor, and Verrecchia 2011). These two measures of private information are complementary as the *GPIN* measure is entirely based on order flows while the *LAMBDA* measure relates unexpected order flows to stock price changes.

The results are reported in Panel B of Table 6. The sample size is reduced for these two measures because both rely on intraday transaction data from the NYSE Trade and Quote (TAQ) database whose coverage starts in 1993. Further, the *GPIN* measure is only computed for NYSE stocks in Duarte, Hu, and Young (2020). In columns 1 and 2 where the dependent variable is the probability of informed trading (*GPIN*), the coefficient on *EDGAR* is significantly negative at the 5% level. The coefficient of -2.833 in column 1 translates into an 11% reduction (relative to its sample mean) in *GPIN*. In columns 3 and 4, we replace the dependent variable with the adverse selection component of the bid-ask spread (*LAMBDA*). Similarly, the coefficient on *EDGAR* is significantly negative at the 1% (5%) level in column 3 (column 4). The coefficient of -0.009 in column 3 translates into a 6% reduction (relative to its sample mean) in *LAMBDA*. The results in Panel B suggest a reduction in privately informed trading after the EDGAR implementation.

Prior research also uses price non-synchronicity as a measure of the amount of private information in prices in equilibrium (Chen, Goldstein, and Jiang 2007). We note that the degree of price non-synchronicity is likely driven by the total amount of firm-specific information in prices (from both public and private sources). The result of increased price non-synchronicity after the EDGAR implementation documented in Gao and Huang (2020) suggests that the total amount of firm-specific information increases: the increase in public information dominates the decrease in private information.

6.4. Value Firms versus Growth Firms

In Panel C of Table 6, we replace *EDGAR* with its interactions with the two firm-type indicators. The coefficient on the interaction term *EDGAR×GROWTH_FIRM* is significantly negative at the 5% level or better in all columns. In contrast, the coefficient on the interaction term *EDGAR×VALUE_FIRM* is statistically insignificant across the board. Further, the difference between the coefficients on these two interaction terms is significant at 10% level or better in all columns. Thus, the results in Panel C suggest that the negative effects of the EDGAR shock on institutional ownership and privately informed trading are concentrated in growth firms.[32]

7. Firm Performance

In this section, we investigate the effect of the EDGAR implementation on *ex post* firm performance. Given the findings in the previous two sections on the equity financing channel and managerial learning channel, we expect that the EDGAR implementation has different effects on the firm performance of value firms and growth firms.

We perform two sets of tests as follows. First, in Panel A of Table 7, we rerun the regression model in Equation (3) by replacing the dependent variable with return on assets (*ROA*) and sales growth (*ΔSALES*). We report the regression results without and with control variables in the odd and even columns, respectively. The coefficient on *EDGAR* is significantly positive at the 1% level in all columns, suggesting that the EDGAR shock has a positive effect on firm profitability and sales growth. In terms of economic significance, the coefficients in columns 1 and 3 (i.e., 0.198 and 2.878) translate into an increase of 12% in *ROA* and 20% in *ΔSALES* (relative to their sample means), respectively.[33]

Second, we rerun the same regression but replace *EDGAR* with *EDGAR×VALUE_FIRM* and *EDGAR×GROWTH_FIRM* in Panel B of Table 7. The coefficient on *EDGAR×VALUE_FIRM* is significantly positive at the 1% level, while the coefficient on *EDGAR×GROWTH_FIRM* is

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[32] We find that the cost-of-capital effect is concentrated in value firms (Table 4 Panel B) while the privately-informed-trading effect is concentrated in growth firms (Table 6 Panel C). One explanation for this difference is that the former result is driven by the increase of common information M' after the EDAGR implantation (mainly for value firms) while the latter result is driven by the decrease of investors' private information N after the EDAGR implantation (mainly for growth firms).

[33] To ensure that these results are not contaminated by survivorship bias, we repeat the analysis in a constant sample of firms that existed for the whole sample period. Our inferences remain unchanged (see Table A7 of the online appendix).

negative and largely statistically insignificant in all columns. The difference between the coefficients on these two interaction terms is significant at the 1% level in all columns. These results show that the observed improvement in firm profitability and sales growth is concentrated in value firms.[34]

Third, we further divide growth firms into high-growth and low-growth firms and include *EDGAR×HIGH_GROWTH_FIRM* and *EDGAR×LOW_GROWTH_FIRM* in the regression models in Panel C of Table 7.[35] The coefficient on *EDGAR×HIGH_GROWTH_FIRM* is significantly negative in all columns, while the coefficient on *EDGAR×LOW_GROWTH_FIRM* is largely statistically insignificant. The difference between the coefficients on these two interaction terms is significant at the 5% level or better in all columns. This significant decline in firm profitability and sales growth in high-growth firms suggests that the negative performance effect of reduced managerial learning dominates the positive performance effect of the EDGAR implementation for these firms.[36]

Collectively, the results in Table 7 reflect the dual effects of greater and broader information dissemination facilitated by modern information technologies. On the one hand, it can better incentivize managers to take value-maximizing actions and improve firm performance. On the other hand, it can hurt firm performance by discouraging privately informed trading and reducing managerial learning from the market. Our evidence suggests that the former effect dominates in value firms while the latter effect dominates in high-growth firms.

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[34] In terms of economic significance, the coefficients on *EDGAR×VALUE_FIRM* in columns 1 and 3 translate into an increase of 32% in *ROA* and 45% in *ΔSALES* (relative to their sample means), respectively.

[35] *HIGH_GROWTH_FIRM* (*LOW_GROWTH_FIRM*) is an indicator that equals one if a growth firm's market-to-book ratio in 1992 is above (below) the median of growth firms, and zero otherwise.

[36] We also repeat our analysis in Table 6 for high-growth and low-growth firms and do not find evidence that the EDGAR implementation differentially reduces privately informed trading for these two types of growth firms. These results suggest that the same degree of reduced managerial learning can be more detrimental to high-growth firms than to low-growth firms.

8. Conclusions

Modern information technologies have greatly facilitated timely dissemination of information to a broad base of investors at low costs. In this paper, we exploit the staggered mandatory implementation of the EDGAR system from 1993 to 1996 as a shock to information dissemination technologies. We find that the EDGAR implementation leads to a 10% increase in the level of corporate investment. The increased level of investment is explained by the findings that broader information dissemination leads to a decrease in the cost of capital and an increase in the level of equity financing. We also find evidence suggesting that greater dissemination of corporate disclosures crowds out private information acquisition and reduces managerial learning from prices. Further, we show that the EDGAR implementation leads to an improvement in performance in value firms but a decline in performance in high-growth firms where learning from the market is particularly important.

Overall, our findings suggest that it is important to consider the tradeoff between financing and learning from prices when evaluating the real effects of modern information technologies. With the rise of FinTech innovation through big data or machine learning techniques, the investing public can now obtain a huge amount of data at relatively low costs (Goldstein, Jiang, and Karolyi 2019). We might reasonably expect the decline in the cost of accessing information to increase forecasting price efficiency. However, our findings suggest that the effect of FinTech innovation on real efficiency is more nuanced as it might dampen investors' incentives to engage in private information acquisition and reduce managerial learning from prices. Moreover, greater information production and dissemination brought by modern technologies may not necessarily enhance the welfare of investors as they can lead to a reduction in risk-sharing and trading opportunities among investors (Hirshleifer 1971; Kurlat and Veldkamp 2015) and an overweight on public signals due to beauty-contest incentives (Morris and Shin 2002). Evaluating these various tradeoffs brought by FinTech developments is an interesting avenue for future research.

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Appendix A: Phase-in Schedule of the EDGAR Implementation

Implementation Date	Group
April 26, 1993	Phase-in of Group CF-01
July 19, 1993	Phase-in of Group CF-02
October 4, 1993	Phase-in of Group CF-03
December 6, 1993	Phase-in of Group CF-04
January 30, 1995	Phase-in of Group CF-05
March 6, 1995	Phase-in of Group CF-06
May 1, 1995	Phase-in of Group CF-07
August 7, 1995	Phase-in of Group CF-08
November 6, 1995	Phase-in of Group CF-09
May 6, 1996	Phase-in of Group CF-10

Note: This table presents the finalized EDGAR implementation dates for the ten phase-in groups (SEC Releases No. 33-6977 and No. 33-7122).

Appendix B: Theoretical Framework for Managerial Learning

Let a representative firm's value be given by $\theta K - \frac{1}{2}K^2$, where K is the total capital, and θ is the random variable that captures the level of productivity of the firm's capital. θ can be interpreted as the firm's fundamentals. Suppose that θ is normally distributed with mean 0 and variance $\frac{1}{\tau_\theta}$. Given the firm's value function, it is easy to see that the firm manager's optimal capital level at time *t* equals the expected level of θ, i.e., $K_t = E(\theta|\text{Manager's Information at } t)$. Changes from K_t to K_{t+1} take the form of investment during period $t+1$. Here, the value function is assumed to be concave in total capital K, and for simplicity, we implicitly assume that adjustments to K are costless. Introducing some adjustment costs will not affect the results qualitatively.

For simplicity and without loss of generality, we focus on a model of two periods: 0 and 1. At $t = 0$, the price of the firm's stock reflects the prior belief about the firm's fundamental θ. The manager of the firm privately observes a signal about θ, denoted as M, where $M = \theta + \varepsilon_M$, and $\varepsilon_M \sim N\,(0, \frac{1}{\tau_M})$. Given her information and using Bayesian updating, the firm's manager will optimally set the level of capital K_0 at: $K_0 = E(\theta|prior, M) = \frac{\tau_M}{\tau_\theta + \tau_M} M$.

At $t = 1$, there are two pieces of information in the marketplace. The first piece of information is a noisy signal about the manager's private information M. We denote this signal as M', where $M' = M + \varepsilon_{M'}$, and $\varepsilon_{M'} \sim N\,(0, \frac{1}{\tau_{M'}})$. The second piece of information is an independent signal about the fundamentals θ. We denote this signal as N, where $N = \theta + \varepsilon_N$, and $\varepsilon_N \sim N\,(0, \frac{1}{\tau_N})$. These two signals reflect the different types of information markets can have. One is information that is already known to the manager (i.e., a signal about the manager's information), and the other is information that is new to the manager (i.e., an independent signal about the fundamentals). Both types of signals can be observed by the market maker in various ways. The most common ways are via the order flows of traders, and via public releases of information. Here we assume for concreteness that both signals are observed by the market maker, who then sets the price to equal the expected level of θ, i.e., $P_t = E(\theta|\text{Market Maker's Information at } t)$.[37] More specifically, $P_1 = E(\theta|prior, M', N) = \frac{\tau_N}{\tau_\theta+\tau_N+\frac{\tau_M \cdot \tau_{M'}}{\tau_M+\tau_{M'}}} N + \frac{\frac{\tau_M \cdot \tau_{M'}}{\tau_M+\tau_{M'}}}{\tau_\theta+\tau_N+\frac{\tau_M \cdot \tau_{M'}}{\tau_M+\tau_{M'}}} M'$.

The manager observes the price (P_1) and the information in the market about her own signal (M'), hence she can infer from price the independent signal in the market about the fundamentals (N). She then optimally sets K_1 at: $K_1 = E(\theta|prior, M, N) = \frac{\tau_N}{\tau_\theta+\tau_N+\tau_M} N + \frac{\tau_M}{\tau_\theta+\tau_N+\tau_M} M$. Then, investment during period $t = 1$ (I_1) is the difference between total capital at $t = 1$ (K_1) and total capital at $t = 0$ (K_0). Hence: $I_1 = \frac{\tau_N}{\tau_\theta+\tau_N+\tau_M} N + \frac{\tau_M}{\tau_\theta+\tau_N+\tau_M} M - \frac{\tau_M}{\tau_\theta+\tau_M} M = \frac{\tau_N}{\tau_\theta+\tau_N+\tau_M}\left(N - \frac{\tau_M}{\tau_\theta+\tau_M} M\right)$.

We are interested in the sensitivity of I_1 to P_1 ($\frac{dI_1}{dP_1}$). As econometricians, we observe I_1 and P_1, but not N or M. To derive the sensitivity of I_1 to P_1, we can write N and M as the products of the following latent linear projections on P_1 : $M = \gamma_M P_1 + e_M$, and $N = \gamma_N P_1 + e_N$. Then, we get: $\frac{dI_1}{dP_1} = \frac{\tau_N}{\tau_\theta+\tau_N+\tau_M}\left(\frac{dN}{dP_1} - \frac{\tau_M}{\tau_\theta+\tau_M}\frac{dM}{dP_1}\right) = \frac{\tau_N}{\tau_\theta+\tau_N+\tau_M}\left(\gamma_N - \frac{\tau_M}{\tau_\theta+\tau_M}\gamma_M\right)$.

By rule of linear projections, $\gamma_N = \frac{Cov(P_1,N)}{Var(P_1)}$ and $\gamma_M = \frac{Cov(P_1,M)}{Var(P_1)}$. Thus, our model predicts: $\frac{dI_1}{dP_1} = \frac{1}{Var(P_1)}\frac{\tau_N}{\tau_\theta+\tau_N+\tau_M}\left(Cov(P_1, N) - \frac{\tau_M}{\tau_\theta+\tau_M} Cov(P_1, M)\right)$. Given the model structure, we can derive expressions for $Var(P_1)$, $Cov(P_1, N)$ and $Cov(P_1, M)$. Substituting these expressions and after some algebra, we get: $\frac{dI_1}{dP_1} = \frac{\tau_N}{\left[\tau_N+\frac{\tau_M \cdot \tau_{M'}}{\tau_M+\tau_{M'}}\right]}\frac{\tau_\theta}{\tau_\theta+\tau_M}$.

The above expression shows that the sensitivity of investment to price (1) is increasing in the precision of the information in the price that is new to the manager (τ_N); (2) is decreasing in the precision of the information in the price that is already known to the manager ($\tau_{M'}$); and (3) is decreasing in the precision of managerial information (τ_M).

[37] For simplicity, we do not model the price as the expected value of the firm, which is itself affected by the price's feedback effect on the manager's action. This simplification follows Subrahmanyam and Titman (1999) and Bai, Philippon, and Savov (2016) and allows us to highlight the real effects of the two different types of information markets can have without getting into more intricate modelling issues. Goldstein and Guembel (2008) and Edmans, Jiang, and Goldstein (2015) develop full-fledged models that consider the price feedback loop.

The intuition behind these results goes as follows: Two types of information affect the price, one is new to the manager, and the other is already known to her. The manager will adjust the optimal capital level (i.e., invest) only upon information in the price that is new to her. The information that was already known to her affected her past capital level and will not affect current investment. Thus, the sensitivity of investment to price will be stronger when movements in the price are more likely to originate from information that is new to the manager than from information that was already known to her. A high precision of new information in the price (which is equivalent to a high amount of new information in the price) will generate a stronger sensitivity of investment to price, while a high precision of old information (which is equivalent to a high amount of old information) will generate a weaker sensitivity. Finally, when the manager's private information is more precise, it is less likely that new information in price changes her expectation about θ and affects her investment decision, resulting in a lower sensitivity of the investment to the price.

Thus, the model suggests that the precision of information in price (or, the amount of total information in price) is not necessarily positively correlated with the investment sensitivity to price. The type of information matters a lot. Overall, we believe the insight is more general than the specific formulation of this model. The distinction between information that is new to managers and information that managers already had is critical. The incorporation of more information of the first type (N in the model) into the price will increase the sensitivity of investment to price, while the incorporation of more information of the second type (M' in the model) will decrease this sensitivity.

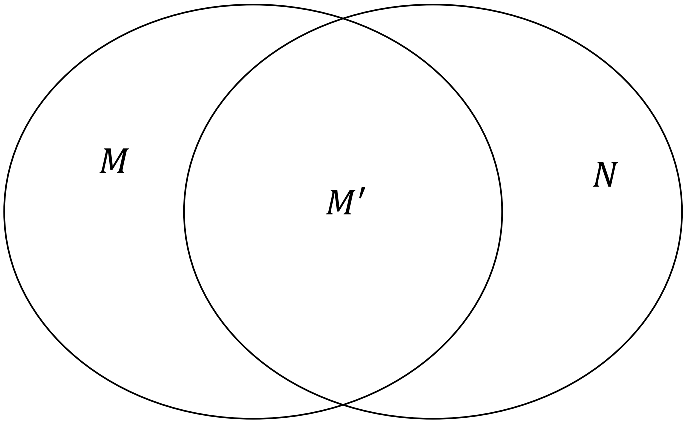
In the empirical setting of the EDGAR implementation, prior research finds that analyst forecast accuracy and stock pricing efficiency increase significantly after a firm becomes an EDGAR filer (Gao and Huang 2020). This result suggests that the precision of information in the marketplace (or, the amount of total information in the marketplace) increases after the EDGAR shock. However, this increase in total information can be entirely driven by the piece of information that is already known to the manager (i.e., M' in the model).[38] Hence, this result does not speak to how the EDGAR shock would affect the amount of information that is new to the manager (N in the model), which is the focus of our empirical analysis.

[38] As noted in the Introduction, increased information dissemination after the EDGAR shock is likely the primary, but not necessarily the only, reason for the change in M' in the marketplace.

Appendix C: Variable Definitions

Variable		Definition
EDGAR	=	An indicator that equals one after a firm becomes a mandatory EDGAR filer, and zero otherwise.
INVESTMENT	=	Capital expenditure scaled by lagged net property, plant, and equipment (PPENTQ). Compustat quarterly data provide the year-to-date amount of net capital expenditure (CAPXY). We therefore set quarterly capital expenditure to be CAPXY (in the first fiscal quarter) or the change in CAPXY (in the second, third, and fourth fiscal quarters). It is expressed in percentage points.
Q	=	The book value of total assets (ATQ) minus the book value of equity (CEQQ) plus the market value of equity (CSHOQ×PRCCQ), scaled by the book value of total assets (ATQ).
SIZE	=	The natural logarithm of the book value of total assets (ATQ).
CF	=	Operating cash flows (IBQ+DPQ) scaled by lagged total assets (ATQ). It is expressed in percentage points.
PRC_INV	=	The inverse of the stock price (PRCCQ) at the fiscal quarter end.
ICC	=	The implied cost of capital measure derived from Gebhardt, Lee, and Swaminathan (2001). It is expressed in percentage points.
EQUITY	=	Equity issuance scaled by lagged total assets (ATQ). Compustat quarterly data provide the year-to-date amount of common and preferred stock issuance (SSTKY). Following Farre-Mensa and Ljungqvist (2016), we set quarterly equity issuance to be SSTKY (in the first fiscal quarter) or the change in SSTKY (in the second, third, and fourth fiscal quarters). It is expressed in percentage points.
GPIN	=	The quarterly average of the conditional probability of private information arrival on a given day estimated in the Generalized PIN model by Duarte, Hu, and Young (2020). It is expressed in percentage points.
LAMBDA	=	The quarterly average of the adverse selection component of the bid-ask spread estimated in Armstrong, Core, Taylor, and Verrecchia (2011) and expressed in percentage points.
INSTOWN	=	Percentage of shares held by institutional investors at the quarter end.
INSTOWN_TRA	=	Percentage of shares held by transient institutional investors at the quarter end. The classification of transient institutional investors is obtained from the institutional investor database developed by Bushee (1998).
VALUE_FIRM	=	An indicator that equals one if a firm's market-to-book ratio in 1992 is below the sample median, and zero otherwise. Market-to-book ratio is defined as the ratio of the market value of a firm's common stock (CSHO×PRCC_F) to its book value (CEQ). It is set to missing if CEQ is negative.
GROWTH_FIRM	=	An indicator that equals one if a firm's market-to-book ratio in 1992 is above the sample median, and zero otherwise.
PRE_MVE	=	The natural logarithm of the market value of equity (CSHO×PRCC_F) in 1992.
ROA	=	The ratio of operating income before depreciation (OIBDPQ) to lagged book value of total assets (ATQ) It is expressed in percentage points.
ΔSALES	=	Growth rate in sales (SALEQ) from the same quarter in the previous year to the current quarter. It is expressed in percentage points.
HIGH_GROWTH_FIRM	=	An indicator that equals one if a growth firm's market-to-book ratio in 1992 is above the median of growth firms, and zero otherwise.
LOW_GROWTH_FIRM	=	An indicator that equals one if a growth firm's market-to-book ratio in 1992 is below the median of growth firms, and zero otherwise.

Figure 1: The Information Sets of Managers and Outside Investors

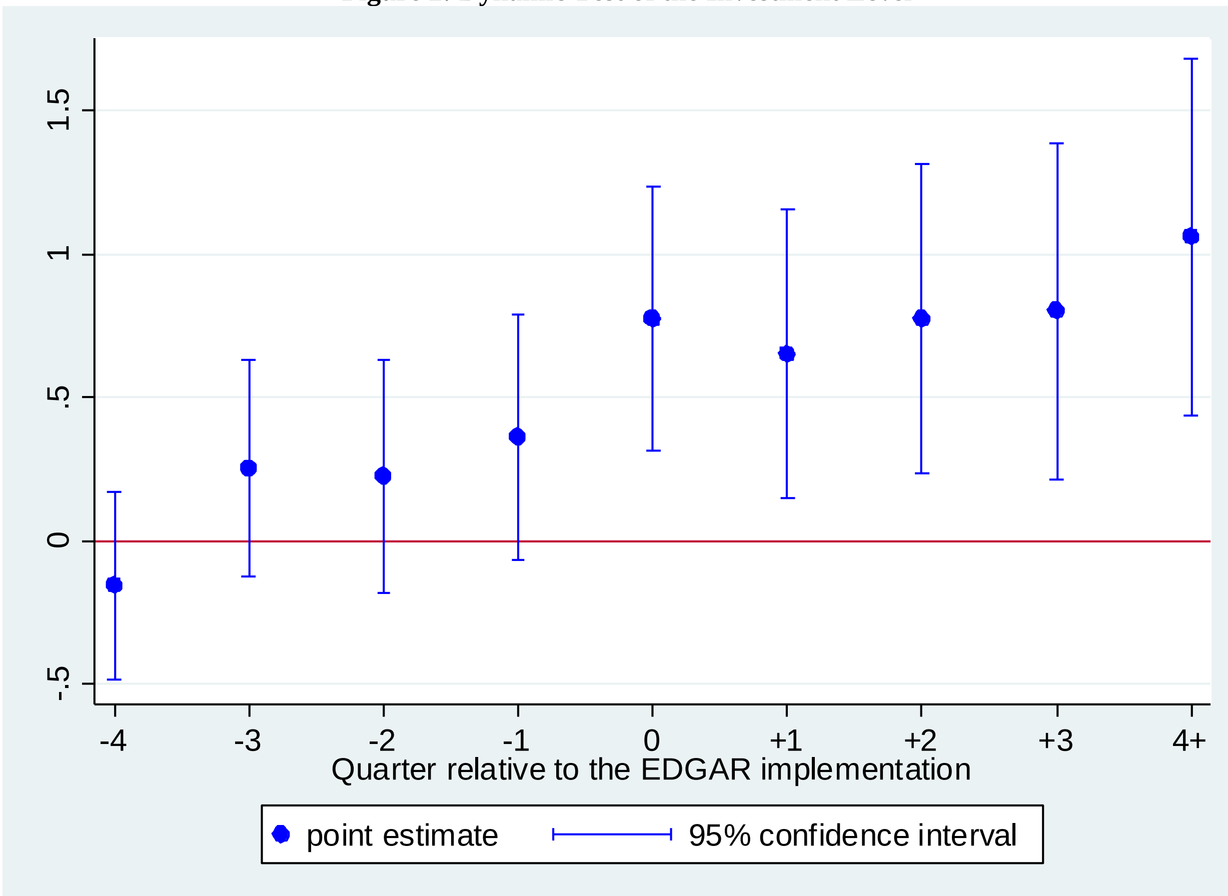


Managers' information sets:
M+M'

Outside investors' information sets:
N+M'

Notes: This figure depicts the information sets of managers and outside investors. M denotes managers' private information, M' denotes common information, and N denotes outside investors' information.

Figure 2: Dynamic Test of the Investment Level



Notes: This figure reports the results from an event-time analysis of the effect of the EDGAR implementation on the level of corporate investment. We re-estimate the regression model on the level of investment in column 1 of Table 2 by replacing *EDGAR* with a set of indicators for the quarters around the EDGAR implementation for each firm in our sample. Specifically, the regression model is as follows:

$$\begin{aligned} INVESTMENT_{i,t} &= \alpha_t + \eta_i + \gamma_1 EDGAR(-4)_{i,t} + \gamma_2 EDGAR(-3)_{i,t} + \gamma_3 EDGAR(-2)_{i,t} + \gamma_4 EDGAR(-1)_{i,t} \\ &+ \gamma_5 EDGAR(0)_{i,t} + \gamma_6 EDGAR(+1)_{i,t} + \gamma_7 EDGAR(+2)_{i,t} + \gamma_8 EDGAR(+3)_{i,t} \\ &+ \gamma_9 EDGAR(4+)_{i,t} + \varepsilon_{i,t} \end{aligned}$$

where $EDGAR(-4)_{i,t}$ ($EDGAR(-3)_{i,t}$, $EDGAR(-2)_{i,t}$, $EDGAR(-1)_{i,t}$) is an indicator that equals one if a firm will become a mandatory EDGAR filer in four quarters (three quarters, two quarters, one quarter), and zero otherwise. $EDGAR(0)_{i,t}$ is an indicator that equals one if a firm becomes a mandatory EDGAR filer in the current quarter *t*, and zero otherwise. $EDGAR(+1)_{i,t}$ ($EDGAR(+2)_{i,t}$, $EDGAR(+3)_{i,t}$) is an indicator that equals one if a firm became a mandatory EDGAR filer one quarter (two quarters, three quarters) ago, and zero otherwise. $EDGAR(4+)_{i,t}$ is an indicator that equals one if a firm became a mandatory EDGAR filer four or more quarters ago, and zero otherwise. The figure reports the coefficient estimates on each event quarter indicator as well as their 95% confidence intervals. The estimation includes firm and year-quarter fixed effects, as well as group-specific trends. The standard errors are clustered at the firm level.

Table 1: Summary Statistics

Variable	N	Mean	Std. Dev.	Q1	Median	Q3
INVESTMENT	66,628	7.090	7.582	2.543	4.867	8.768
EDGAR	66,628	0.494	0.500	0.000	0.000	1.000
Q	66,628	1.803	1.215	1.086	1.412	2.037
CF	66,628	1.708	4.394	0.966	2.374	3.759
SIZE	66,628	5.106	1.760	3.770	4.861	6.241
PRC_INV	66,628	0.222	0.477	0.041	0.081	0.186
ICC	38,166	10.431	3.283	8.467	10.266	12.151
EQUITY	64,335	1.001	5.058	0.000	0.012	0.183
GPIN	12,283	25.066	18.164	13.842	20.510	29.987
LAMBDA	41,543	0.157	0.164	0.056	0.116	0.213
INSTOWN	66,141	33.163	24.349	11.352	31.043	52.693
INSTOWN_TRA	66,141	6.032	7.537	0.252	3.155	9.031
ROA	66,094	1.624	4.154	0.448	2.089	3.665
ΔSALES	65,477	14.713	40.855	-2.558	7.954	22.379

Notes: This table presents the summary statistics for the variables used in our main analysis. The sample period starts in the second quarter of 1991 and ends in the second quarter of 1998. All continuous variables are winsorized at the top and bottom one percent to mitigate the influence of extreme values. Variable definitions are provided in Appendix C.

Table 2: Main Results on Corporate Investment

Panel A: Baseline Analysis

Dependent Variable =	*INVESTMENT*	
	(1)	(2)
EDGAR	**0.613***** **(4.05)**	**0.403***** **(2.84)**
Q		1.714*** (18.97)
CF		0.178*** (12.94)
SIZE		0.354** (2.10)
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	66,628	66,628
Adjusted *R*-squared	0.272	0.302

Panel B: Controlling for Group-Specific Trends

Dependent Variable =	*INVESTMENT*	
	(1)	(2)
EDGAR	**0.535***** **(3.59)**	**0.344**** **(2.46)**
Q		1.621*** (18.46)
CF		0.169*** (12.69)
SIZE		0.562*** (3.33)
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Group-Specific Trends	Yes	Yes
Observations	66,628	66,628
Adjusted *R*-squared	0.281	0.308

Panel C: Stacked Diff-in-Diff Regression

Dependent Variable =	*INVESTMENT*	
	(1)	(2)
EDGAR	**0.506***** **(2.79)**	**0.445**** **(2.52)**
Q		1.483*** (9.63)
CF		0.086*** (5.43)
SIZE		0.511* (1.78)
Group-Specific Firm FE	Yes	Yes
Group-Specific Year-Quarter FE	Yes	Yes
Observations	31,319	31,319
Adjusted *R*-squared	0.362	0.374

Notes: This table reports the regression results on corporate investment. The dependent variable is the quarterly investment made by the firm (*INVESTMENT*), defined as capital expenditure in the next quarter scaled by the net property, plant, and equipment at the current quarter end. *EDGAR* is an indicator that equals one after a firm becomes a mandatory EDGAR filer, and zero otherwise. *Q* is Tobin's Q. All other variables are defined in Appendix C. In Panel A, we report the regression results using the baseline model. In Panel B, we control for group-specific time trends. In Panel C, we run a stacked diff-in-diff regression with a matched sample, where treated firms are from groups CF-01 through CF-07 and control firms are selected from the set of to-be-treated firms using a nearest-neighbor propensity-score method for each group. Treated firms are tracked in the window of event quarters [-4, +4], with quarter 0 being the EDGAR implementation quarter. We match treated and controls on three dimensions (i.e., *Q*, *CF*, and *SIZE*) in the quarter before the EDGAR implementation. The *t*-statistics of robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Value Firms versus Growth Firms

Panel A: Baseline Analysis

Dependent Variable =	*INVESTMENT*	
	(1)	(2)
***EDGAR×VALUE_FIRM* (a)**	**1.384*** **	**0.899*** **
	(7.74)	**(5.35)**
***EDGAR×GROWTH_FIRM* (b)**	**-0.123**	**-0.051**
	(-0.68)	**(-0.30)**
Q		1.721***
		(18.49)
CF		0.174***
		(12.09)
SIZE		0.473***
		(2.62)
Test of (a)=(b) (*p*-value)	**<0.001**	**<0.001**
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	62,441	62,441
Adjusted *R*-squared	0.273	0.304

Panel B: Controlling for Pre-Size Effects

Dependent Variable =	*INVESTMENT*	
	(1)	(2)
***EDGAR×VALUE_FIRM* (a)**	**1.472*** **	**0.910*** **
	(5.49)	**(3.66)**
***EDGAR×GROWTH_FIRM* (b)**	**-0.004**	**-0.035**
	(-0.01)	**(-0.11)**
Q		1.721***
		(18.49)
CF		0.174***
		(12.09)
SIZE		0.473***
		(2.62)
EDGAR×PRE_MVE	-0.021	-0.003
	(-0.44)	(-0.06)
Test of (a)=(b) (*p*-value)	**<0.001**	**<0.001**
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	62,441	62,441
Adjusted *R*-squared	0.277	0.304

Notes: This table reports the regression results for the differential treatment effects in value firms and growth firms. The dependent variable is the quarterly investment made by the firm (*INVESTMENT*), defined as capital expenditure in the next quarter scaled by the net property, plant, and equipment at the current quarter end. *VALUE_FIRM* (*GROWTH_FIRM*) is an indicator that equals one if a firm's market-to-book ratio in 1992 is below (above) the median, and zero otherwise. *EDGAR* is an indicator that equals one after a firm becomes a mandatory EDGAR filer, and zero otherwise. *Q* is Tobin's Q. *PRE_MVE* is the natural logarithm of the market value of equity in 1992. All other variables are defined in Appendix C. Reflecting the signed nature of the predictions, the test for equal treatment effects is one-sided. The *t*-statistics of robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Equity Financing Channel

Panel A: Baseline Analysis				
Dependent Variable =	*ICC*		*EQUITY*	
	(1)	(2)	(3)	(4)
EDGAR	**-0.195****	**-0.168****	**0.294*****	**0.253*****
	(-2.55)	**(-2.29)**	**(3.20)**	**(2.83)**
SIZE		0.488***		-1.999***
		(4.88)		(-16.33)
PRC_INV		7.501***		-1.214***
		(8.42)		(-11.18)
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	38,166	38,166	64,335	64,335
Adjusted *R*-squared	0.604	0.627	0.088	0.107

Panel B: Value Firms versus Growth Firms				
Dependent Variable =	*ICC*		*EQUITY*	
	(1)	(2)	(3)	(4)
***EDGAR×VALUE_FIRM* (a)**	**-0.622*****	**-0.422****	**0.490*****	**0.506*****
	(-6.44)	**(-2.25)**	**(4.79)**	**(3.88)**
***EDGAR×GROWTH_FIRM* (b)**	**0.103**	**0.348**	**0.052**	**0.073**
	(1.23)	**(1.64)**	**(0.48)**	**(0.42)**
EDGAR×PRE_MVE		-0.041		-0.004
		(-1.30)		(-0.19)
Test of (a)=(b) (*p*-value)	**<0.001**	**<0.001**	**<0.001**	**<0.001**
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	36,901	36,901	60,335	60,335
Adjusted *R*-squared	0.610	0.633	0.090	0.090

Notes: This table reports the regression results on the equity financing channel. The dependent variables include the implied cost of capital (*ICC*) and the amount of equity issuance (*EQUITY*). *EDGAR* is an indicator that equals one after a firm becomes a mandatory EDGAR filer, and zero otherwise. *VALUE_FIRM* (*GROWTH_FIRM*) is an indicator that equals one if a firm's market-to-book ratio in 1992 is below (above) the median, and zero otherwise. *PRE_MVE* is the natural logarithm of the market value of equity in 1992. All other variables are defined in Appendix C. Reflecting the signed nature of the predictions, the test for equal treatment effects is one-sided. The *t*-statistics of robust standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Managerial Learning Channel: Investment-to-Price Sensitivity

Panel A: Baseline Analysis

Dependent Variable =	*INVESTMENT*		
	(1)	(2)	(3)
EDGAR	0.933***	0.923***	1.510**
	(3.09)	(2.67)	(2.54)
Q	1.908***	1.490***	1.614***
	(18.64)	(8.48)	(10.20)
CF	0.136***	0.091***	0.054***
	(7.34)	(4.69)	(3.16)
SIZE	0.381**	0.468**	0.541*
	(2.23)	(2.23)	(1.86)
Q×EDGAR	**-0.392*** **	**-0.234***	**-0.295***
	(-3.90)	**(-1.99)**	**(-2.05)**
CF×EDGAR	0.081***	0.069***	0.117***
	(3.35)	(2.92)	(3.90)
SIZE×EDGAR	0.004	-0.054	-0.154
	(0.08)	(-1.02)	(-1.54)
Firm FE	Yes	Yes	No
Year-Quarter FE	Yes	Yes	No
Q×Firm FE	No	Yes	No
Group-Specific Firm FE	No	No	Yes
Group-Specific Year-Quarter FE	No	No	Yes
Observations	66,628	66,628	31,319
Adjusted R-squared	0.304	0.346	0.375

Panel B: Value Firms versus Growth Firms

Dependent Variable =	*INVESTMENT*	
	(1)	(2)
EDGAR	0.405***	0.938***
	(2.82)	(3.71)
CF	0.173***	0.170***
	(11.88)	(11.83)
SIZE	0.357**	0.477***
	(2.01)	(2.64)
Q×VALUE_FIRM	2.378***	2.444***
	(10.72)	(10.35)
Q×GROWTH_FIRM	1.592***	1.754***
	(15.40)	(15.20)
***Q×VALUE_FIRM×EDGAR* (a)**		**-0.206**
		(-1.08)
***Q×GROWTH_FIRM×EDGAR* (b)**		**-0.371*** **
		(-3.41)
Test of (a)=(b) (*p*-value)		**0.111**
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	62,441	62,441
Adjusted R-squared	0.303	0.304

Notes: This table reports the regression results on the investment-to-price sensitivity. The dependent variable is the quarterly investment made by the firm (*INVESTMENT*), defined as capital expenditure in the next quarter scaled by the net property, plant, and equipment at the current quarter end. *EDGAR* is an indicator that equals one after a firm becomes a mandatory EDGAR filer, and zero otherwise. *Q* is Tobin's Q. All other variables are defined in Appendix C. In column 1 of Panel A, we report the regression results using the baseline model. In column 2 of Panel A, we control for *Q* times firm fixed effects. In column 3 of Panel A, we run a stacked diff-in-diff regression with a matched sample, where treated firms are from groups CF-01 through CF-07 and control firms are selected from the set of to-be-treated firms using a nearest-neighbor propensity-score method for each group. Treated firms are tracked in the window of event quarters [-4, +4], with quarter 0 being the EDGAR implementation quarter. We match treated and controls on three dimensions (i.e., *Q*, *CF*, and *SIZE*) in the quarter before the EDGAR implementation. In Panel B, *VALUE_FIRM* (*GROWTH_FIRM*) is an indicator that equals one if a firm's market-to-book ratio in 1992 is below (above) the median, and zero otherwise. Reflecting the signed nature of the predictions, the test for equal treatment effects is one-sided. The *t*-statistics of robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Managerial Learning Channel: Institutional Ownership and Privately Informed Trading

Panel A: Institutional Ownership

Dependent Variable =	*INSTOWN*		*INSTOWN_TRA*	
	(1)	(2)	(3)	(4)
EDGAR	**-0.720****	**-0.551***	**-0.380****	**-0.349****
	(-2.46)	**(-1.96)**	**(-2.37)**	**(-2.19)**
SIZE		6.062***		0.890***
		(15.47)		(5.27)
PRC_INV		-5.801***		-1.984***
		(-11.11)		(-11.96)
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	66,141	66,141	66,141	66,141
Adjusted *R*-squared	0.844	0.857	0.554	0.562

Panel B: Privately Informed Trading

Dependent Variable =	*GPIN*		*LAMBDA*	
	(1)	(2)	(3)	(4)
EDGAR	**-2.833****	**-2.839****	**-0.009*****	**-0.007****
	(-2.09)	**(-2.08)**	**(-2.77)**	**(-2.35)**
SIZE		-0.118		-0.030***
		(-0.10)		(-7.42)
PRC_INV		2.921		0.039***
		(0.79)		(3.59)
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	12,283	12,283	41,543	41,543
Adjusted *R*-squared	0.172	0.172	0.359	0.363

Panel C: Value Firms versus Growth Firms

Dependent Variable =	*INSTOWN*	*INSTOWN_TRA*	*GPIN*	*LAMBDA*
	(1)	(2)	(3)	(4)
***EDGAR×VALUE_FIRM* (a)**	**-0.196**	**-0.055**	**-1.725**	**-0.000**
	(-0.52)	**(-0.29)**	**(-1.25)**	**(-0.09)**
***EDGAR×GROWTH_FIRM* (b)**	**-0.942*****	**-0.824*****	**-4.206****	**-0.018*****
	(-2.73)	**(-4.23)**	**(-2.45)**	**(-4.62)**
Test of (a)=(b) (*p*-value)	**0.056**	**<0.001**	**0.048**	**<0.001**
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	62,096	62,096	12,112	39,124
Adjusted *R*-squared	0.851	0.558	0.173	0.357

Notes: This table reports the regression results on the managerial learning channel. In Panel A, the dependent variables include total institutional ownership (*INSTOWN*) and transient institutional ownership (*INSTOWN_TRA*). In Panel B, the dependent variables include the probability of informed trading (*GPIN*) and the adverse selection component of the bid-ask spread (*LAMBDA*). In Panel C, *VALUE_FIRM* (*GROWTH_FIRM*) is an indicator that equals one if a firm's market-to-book ratio in 1992 is below (above) the median, and zero otherwise. *EDGAR* is an indicator that equals one after a firm becomes a mandatory EDGAR filer, and zero otherwise. All other variables are defined in Appendix C. Reflecting the signed nature of the predictions, the test for equal treatment effects is one-sided. The *t*-statistics of robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Firm Performance

Panel A: Baseline Analysis				
Dependent Variable =	*ROA*		*ΔSALES*	
	(1)	(2)	(3)	(4)
EDGAR	**0.198*****	**0.200*****	**2.878*****	**2.989*****
	(3.07)	**(3.12)**	**(2.89)**	**(3.01)**
SIZE		-0.054		2.220*
		(-0.61)		(1.78)
PRC_INV		-0.853***		-9.984***
		(-8.79)		(-8.35)
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	66,094	66,094	65,477	65,477
Adjusted R-squared	0.557	0.560	0.179	0.184

Panel B: Value Firms versus Growth Firms				
Dependent Variable =	*ROA*		*ΔSALES*	
	(1)	(2)	(3)	(4)
***EDGAR×VALUE_FIRM* (a)**	**0.515*****	**0.367****	**6.650*****	**5.480*****
	(6.23)	**(2.57)**	**(5.52)**	**(3.31)**
***EDGAR×GROWTH_FIRM* (b)**	**-0.111**	**-0.311***	**-0.172**	**-1.757**
	(-1.34)	**(-1.67)**	**(-0.15)**	**(-0.84)**
EDGAR×PRE_MVE		0.036		0.284
		(1.31)		(0.96)
Test of (a)=(b) (*p*-value)	**<0.001**	**<0.001**	**<0.001**	**<0.001**
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	62,054	62,054	61,461	61,461
Adjusted R-squared	0.562	0.562	0.177	0.177

Panel C: High versus Low Growth Firms				
Dependent Variable =	*ROA*		*ΔSALES*	
	(1)	(2)	(3)	(4)
EDGAR×VALUE_FIRM	0.516***	0.339**	6.668***	5.098***
	(6.23)	(2.36)	(5.53)	(3.08)
***EDGAR×LOW_GROWTH_FIRM* (a)**	**0.069**	**-0.161**	**2.271***	**0.226**
	(0.68)	**(-0.87)**	**(1.69)**	**(0.11)**
***EDGAR×HIGH_GROWTH_FIRM* (b)**	**-0.290****	**-0.539****	**-2.617***	**-4.825****
	(-2.29)	**(-2.39)**	**(-1.75)**	**(-1.99)**
EDGAR×PRE_MVE		0.043		0.382
		(1.54)		(1.28)
Test of (a)=(b) (*p*-value)	**0.012**	**0.009**	**0.002**	**0.001**
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	62,054	62,054	61,461	61,461
Adjusted R-squared	0.562	0.562	0.178	0.178

Notes: This table reports the regression results on firm performance. The dependent variables include return on assets (*ROA*) and sales growth (*ΔSALES*). *EDGAR* is an indicator that equals one after a firm becomes a mandatory EDGAR filer, and zero otherwise. *VALUE_FIRM* (*GROWTH_FIRM*) is an indicator that equals one if a firm's market-to-book ratio in 1992 is below (above) the median, and zero otherwise. *LOW_GROWTH_FIRM* (*HIGH_GROWTH_FIRM*) is an indicator that equals one if a growth firm's market-to-book ratio in 1992 is below (above) the median of growth firms, and zero otherwise. *PRE_MVE* is the natural logarithm of the market value of equity in 1992. All other variables are defined in Appendix C. Reflecting the signed nature of the predictions, the test for equal treatment effects is one-sided. The *t*-statistics of robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Online Appendix for

The Real Effects of Modern Information Technologies: Evidence from the EDGAR Implementation

Table A1: An Alternative Proxy for Firm Size

Dependent Variable =	*INVESTMENT*	
	(1)	(2)
EDGAR	**0.613******	**0.406******
	(4.05)	**(2.90)**
Q		1.118***
		(10.59)
CF		0.136***
		(10.17)
MVE		1.538***
		(13.96)
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	66,628	66,628
Adjusted *R*-squared	0.272	0.311

Notes: This table reports the regression results on corporate investment with an alternative proxy for firm size, i.e., the natural logarithm of market capitalization (*MVE*). The dependent variable is the quarterly investment made by the firm (*INVESTMENT*), defined as capital expenditure in the next quarter scaled by the net property, plant, and equipment at the current quarter end. *EDGAR* is an indicator that equals one after a firm becomes a mandatory EDGAR filer, and zero otherwise. *Q* is Tobin's Q. All other variables are defined in Appendix C. The *t*-statistics of robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A2: Removal of Transitional Filers

Dependent Variable =	*INVESTMENT*	
	(1)	(2)
EDGAR	**0.717******	**0.488******
	(4.60)	**(3.32)**
Q		1.711***
		(18.77)
CF		0.178***
		(12.81)
SIZE		0.353**
		(2.07)
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	64,612	64,612
Adjusted *R*-squared	0.271	0.301

Notes: This table reports the regression results on corporate investment after excluding firms assigned to Group CF-01 (i.e., the first group) as this group contains "transitional" filers that volunteered to file electronically prior to the mandatory phase-in of the EDGAR system in April 1993. The dependent variable is the quarterly investment made by the firm (*INVESTMENT*), defined as capital expenditure in the next quarter scaled by the net property, plant, and equipment at the current quarter end. *EDGAR* is an indicator that equals one after a firm becomes a mandatory EDGAR filer, and zero otherwise. *Q* is Tobin's Q. All other variables are defined in Appendix C. The *t*-statistics of robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A3: Requirement of Free Online Access

Dependent Variable =	*INVESTMENT*	
	(1)	(2)
EDGAR	**0.803***** **(4.84)**	**0.532***** **(3.39)**
Q		1.712*** (18.95)
CF		0.177*** (12.93)
SIZE		0.356** (2.12)
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	66,628	66,628
Adjusted *R*-squared	0.272	0.302

Notes: This table reports the regression results on corporate investment after redefining the *EDGAR* indicator for groups CF-01 through CF-04 (i.e., the first four groups) to take the value of one if the firm-quarter is after January 17, 1994 (when all electronic EDGAR filings became freely available online via a National Science Foundation grant to New York University) and zero otherwise. *EDGAR* for the remaining six groups is an indicator that equals one after a firm becomes a mandatory EDGAR filer, and zero otherwise. The dependent variable is the quarterly investment made by the firm (*INVESTMENT*), defined as capital expenditure in the next quarter scaled by the net property, plant, and equipment at the current quarter end. *Q* is Tobin's Q. All other variables are defined in Appendix C. The *t*-statistics of robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A4: Stock Liquidity

Panel A: Baseline Analysis				
Dependent Variable =	*SPREAD*		*HL_SPREAD*	
	(1)	(2)	(3)	(4)
EDGAR	**-0.444*****	**-0.384*****	**-0.278*****	**-0.257*****
	(-5.90)	**(-6.17)**	**(-6.90)**	**(-7.82)**
SIZE		-0.628***		-0.116***
		(-7.51)		(-3.28)
PRC_INV		5.860***		3.466***
		(25.36)		(32.19)
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	55,737	55,465	63,972	63,972
Adjusted *R*-squared	0.676	0.752	0.677	0.760

Panel B: Value Firms versus Growth Firms				
Dependent Variable =	*SPREAD*		*HL_SPREAD*	
	(1)	(2)	(3)	(4)
EDGAR×VALUE_FIRM **(a)**	**-0.516*****	**-2.017*****	**-0.436*****	**-1.654*****
	(-4.78)	**(-8.33)**	**(-8.42)**	**(-15.77)**
EDGAR×GROWTH_FIRM **(b)**	**-0.230****	**-2.269*****	**-0.071**	**-1.709*****
	(-2.54)	**(-8.17)**	**(-1.42)**	**(-13.87)**
EDGAR×PRE_MVE		0.393***		0.296***
		(8.22)		(14.72)
Test of (a)=(b) (*p*-value)	**0.017**	**0.033**	**<0.001**	**0.188**
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	52,678	52,678	60,441	60,441
Adjusted *R*-squared	0.681	0.684	0.681	0.689

Notes: This table reports the regression results on stock liquidity. The dependent variables include the simple bid-ask spread (*SPREAD*) and the high-low spread estimator (*HL_SPREAD*) developed by Corwin and Schultz (2012). Both dependent variables are expressed in percentage points. *EDGAR* is an indicator that equals one after a firm becomes a mandatory EDGAR filer, and zero otherwise. *VALUE_FIRM* (*GROWTH_FIRM*) is an indicator that equals one if a firm's market-to-book ratio in 1992 is below (above) the median, and zero otherwise. *PRE_MVE* is the natural logarithm of the market value of equity in 1992. All other variables are defined in Appendix C. Reflecting the signed nature of the predictions, the test for equal treatment effects is one-sided. The *t*-statistics of robust standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A5: Debt Financing

Dependent Variable =	*DEBT*	
	(1)	(2)
EDGAR	**-0.101**	**-0.111**
	(-1.34)	**(-1.46)**
SIZE		-0.490***
		(-6.05)
PRC_INV		-0.456***
		(-5.03)
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	65,672	65,672
Adjusted *R*-squared	0.026	0.028

Notes: This table reports the regression results on debt financing. The dependent variable is the amount of debt issuance (*DEBT*). We define *DEBT* as net debt issuance (DLTISQ minus DLTRQ) scaled by lag total assets (ATQ); when DLTISQ and DLTRQ are missing, this variable equals the change in total debt for the company (change in DLTTQ plus change in DLCQ) scaled by lag total assets. *DEBT* is expressed in percentage points. *EDGAR* is an indicator that equals one after a firm becomes a mandatory EDGAR filer, and zero otherwise. All other variables are defined in Appendix C. The *t*-statistics of robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A6: Quasi-Indexers and Dedicated Institutional Investors

Dependent Variable =	*INSTOWN_QIX*		*INSTOWN_DED*	
	(1)	(2)	(3)	(4)
EDGAR	**-0.816***** **(-4.92)**	**-0.734***** **(-4.51)**	**0.417**** **(2.35)**	**0.467***** **(2.66)**
SIZE		3.183*** (16.80)		1.804*** (9.06)
PRC_INV		-1.769*** (-9.25)		-1.735*** (-6.78)
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	66,141	66,141	66,141	66,141
Adjusted *R*-squared	0.819	0.827	0.670	0.676

Notes: This table repeats the regression of Panel A of Table 6 for the other two types of institutional investors: quasi-indexers (who use indexing or buy-and-hold strategies characterized by high diversification and low portfolio turnover) and dedicated institutional investors (who have large, long-term holdings concentrated in only a few firms). The dependent variables include the percentage of shares held by quasi-indexers (*INSTOWN_QIX*) and the percentage of shares held by dedicated institutional investors (*INSTOWN_ DED*). *EDGAR* is an indicator that equals one after a firm becomes a mandatory EDGAR filer, and zero otherwise. All other variables are defined in Appendix C. The *t*-statistics of robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A7: Constant Sample

Dependent Variable =	*ROA*		*ΔSALES*	
	(1)	(2)	(3)	(4)
EDGAR	**0.186*** **	**0.197*** **	**2.949*** **	**3.125*** **
	(2.63)	**(2.79)**	**(2.66)**	**(2.82)**
SIZE		-0.018		1.968
		(-0.18)		(1.46)
PRC_INV		-0.895***		-10.788***
		(-7.97)		(-7.85)
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	54,410	54,410	53,928	53,928
Adjusted *R*-squared	0.563	0.567	0.165	0.170

Notes: This table reports the regression results on firm performance using a constant sample of firms that existed for the whole sample period. The dependent variables include return on assets (*ROA*) and sales growth (*ΔSALES*). *EDGAR* is an indicator that equals one after a firm becomes a mandatory EDGAR filer, and zero otherwise. All other variables are defined in Appendix C. The *t*-statistics of robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.