NBER WORKING PAPER SERIES

THE REAL EFFECTS OF MODERN INFORMATION TECHNOLOGIES

Itay Goldstein
Shijie Yang
Luo Zuo

Working Paper 27529
http://www.nber.org/papers/w27529

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2020

We gratefully acknowledge helpful comments from John Core, Eric So, Rodrigo Verdi, Joseph Weber, and seminar participants at the Massachusetts Institute of Technology. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

The Real Effects of Modern Information Technologies
Itay Goldstein, Shijie Yang, and Luo Zuo
NBER Working Paper No. 27529
July 2020
JEL No. G12,G14,G31,M41

ABSTRACT

Modern information technologies have greatly facilitated timely dissemination of information to a broad base of investors at low costs. To examine their effects on the real economy, we exploit the staggered implementation of the EDGAR system from 1993 to 1996 as a shock to information dissemination technologies. We find that the EDGAR implementation leads to an increase in the level of corporate investment but a decrease in the investment-to-price sensitivity. We provide evidence that improved equity financing and reduced managerial learning from prices are the underlying mechanisms that explain these real effects, respectively. In addition, 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.

Itay Goldstein
The Wharton School
University of Pennsylvania
3620 Locust Walk
Philadelphia, PA 19104
and NBER
itayg@wharton.upenn.edu

Shijie Yang
The Chinese University of
Hong Kong, Shenzhen
Room 606, Zhi Ren Building
2001 Longxiang Road, Longgang District
Shenzhen, Guangdong 518172
China
sjyang@cuhk.edu.cn

Luo Zuo
Johnson Graduate School of Management
Cornell University
114 East Avenue
349 Sage Hall
Ithaca, NY 14853
luozuo@cornell.edu

1. Introduction

A fundamental question in financial economics is whether and how information disclosure in financial markets affects the real economy (Goldstein and Yang 2017). To understand this question, a large literature in accounting and finance has developed to examine the effects of financial reporting and disclosure on corporate investment (Roychowdhury, Shroff, and Verdi 2019). Prior research on the real effects of corporate disclosures often assumes that accounting information, once disclosed by a firm, is costlessly disseminated and equally available to the investing public. However, a different line of research shows that the costs of monitoring for, acquiring, and analyzing firm disclosures can be substantial (Lee and So 2015; Blankespoor, deHaan, and Marinovic 2020). In this paper, we examine whether and how investors' costs of accessing firm disclosures affect corporate investment by exploiting the emergence of modern information technologies that reduce these costs.

Modern information technologies have greatly facilitated timely dissemination of information to a broad base of investors at low costs (Gao and Huang 2020). With technological advances, the U.S. Securities and Exchange Commission (SEC) has implemented a series of regulatory changes to improve the public's accessibility of firm disclosures. For example, in 1993 the SEC began to mandate electronic submission of corporate filings through the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system, and in 2013 the SEC allowed companies to use social media outlets (e.g., Facebook and Twitter) to announce key information. We argue that these fundamental changes in information dissemination brought by modern information technologies affect corporate investment through two channels: (1) the equity financing channel (in the primary market), and (2) the managerial learning channel (in the secondary market).[1]

[1] Most trading in financial markets occurs in secondary markets after new capital issuance has already happened in primary markets (Bond, Edmans, and Goldstein 2012).

To identify these real effects and the underlying mechanisms, 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 2020). We aim to understand whether and how the EDGAR implementation affects both the level of corporate investment and the investment sensitivity to stock prices. We develop two main hypotheses.

Our first hypothesis is that the EDGAR implementation leads to an increase in the level of corporate investment through the equity financing channel. This hypothesis follows from the conventional wisdom that greater and broader information dissemination leads to an increase in the amount of total information in the marketplace, which improves the functioning of the financial market and firms' access to external capital, thereby allowing firms to tap into new investment opportunities.

Improved equity financing after the EDGAR implementation can arise for at least three reasons. First, more timely and extensive dissemination of firm disclosures can reduce adverse selection problems resulting from information asymmetry between the firm and new investors in the primary market (Myers and Majluf 1984). Second, broad information dissemination levels the playing field, mitigates information asymmetry among investors, attracts liquidity to the secondary market, and eventually results in a lower cost of capital in the primary market (Merton 1987; Diamond and Verrecchia 1991). Third, a firm's commitment for timely dissemination of information regarding managers' actions after equity issuance alleviates investors' *ex ante* concern about *ex post* moral hazard costs and increases their willingness to provide financing to firms (Jensen and Meckling 1976; Holmström 1979; Watts and Zimmerman 1986). While it is difficult to empirically separate these different explanations, they point to the same prediction that reduced costs of accessing firm disclosures lead to an increased level of equity financing and investment.

Our second hypothesis is that the EDGAR implementation affects the sensitivity of corporate investment to stock prices through the managerial learning channel. The idea that prices are a useful source of information goes back to Hayek (1945).[2] Stock prices can reveal traders' private information that is otherwise not available to managers (Grossman and Stiglitz 1980; Glosten and Milgrom 1985; Kyle 1985; Easley and O'Hara 1987), and hence can affect managers' forecasts about their own firms' fundamentals (Zuo 2016; Jayaraman and Wu 2020) and their investment decisions (Luo 2005; Chen, Goldstein, and Jiang 2007).[3] The managerial learning perspective (see Bond, Edmans, and Goldstein (2012) for a review) predicts that the investment-to-price sensitivity depends on the extent to which prices reveal new information to managers (i.e., revelatory price efficiency), which can be and is often different from the extent to which prices reflect all available information (i.e., forecasting price efficiency). We develop a stylized model in our paper to illustrate the basic mechanism underlying this general prediction.

Under this perspective, whether the EDGAR implementation enhances or impedes managerial learning depends on its net effect on revelatory price efficiency.[4] Theories predict two opposite effects. On the one hand, the EDGAR system naturally leads to more aggressive trading on information from corporate disclosures, which can reduce uncertainty in trading on other

---

[2] 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 …" In his testimony before Congress in 1994, George Soros (a prominent trader) stated: "In certain circumstances, financial markets can affect the so-called fundamentals which they are supposed to reflect."

[3] 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).

[4] Traditional models predict that a decline in information acquisition costs leads to an increase in forecasting price efficiency (Verrecchia 1982; Diamond 1985). Gao and Huang (2020) provide evidence supporting this prediction.

fundamental information and encourage more acquisition and trading of information potentially unknown to managers, resulting in a crowding-in effect (Goldstein and Yang 2015). 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 (Dugast and Foucault 2018). 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. Given these theoretical tensions, how the EDGAR implementation affects managerial learning and the investment-to-price sensitivity is therefore an empirical question.

To test our hypotheses, we exploit the staggered nature of the implementation of the EDGAR system. On February 23, 1993, the 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 filers in April 1993 and May 1996, respectively. This staggered mandatory implementation of the EDGAR system reduces potential endogeneity concern 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 differences-in-differences (diff-in-diff) research design, we find that the EDGAR implementation leads to a 10% increase in the level of corporate investment but a 20% decrease in the investment-to-price sensitivity.[5] A standard dynamic test shows no difference in pre-trends in investment behavior between the treatment and control groups, supporting the parallel-trends assumption.

[5] Greater financing and stronger governance after the EDAGR implementation can lead to an increase in the investment-to-price sensitivity. Thus, the observed decrease in the investment-to-price sensitivity is unlikely to be driven by these alternative channels.

We conduct two sets of analyses to understand the underlying mechanisms. First, we examine the equity financing channel. We show that, after a firm becomes an EDGAR filer, the firm's stock becomes more liquid and less volatile and the firm obtains more equity financing. These results are consistent with our prediction that EDGAR inclusion improves firms' information environments, access to equity capital, and ability to undertake investment projects.

Second, we examine the managerial learning channel. The observed decrease in the investment-to-price sensitivity suggests reduced managerial learning from the market after EDGAR inclusion. We argue that this reduction in learning happens because greater dissemination of corporate disclosures levels the playing field, discourages private information acquisition, and crowds out some information that is new to managers. We first 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.

To provide further empirical support to this argument, we use two measures based on structural market microstructure models to assess the equilibrium level of private information in prices. The first measure is the probability of informed trading based on the Generalized PIN model recently developed in Duarte, Hu, and Young (2020), and the second measure is the adverse selection component of the bid-ask spread (Madhavan, Richardson, and Roomans 1997; Armstrong, Core, Taylor, and Verrecchia 2011). These two measures are complementary as the former relies on order flows to identify private information arrival while the latter directly measures the extent to which prices are affected by unexpected order flows. We show that the EDGAR implementation leads to a decrease in both measures of private information.

Next, we explore cross-sectional differences between firms to provide a tighter link between investors' private information and managerial learning. The condition for managerial learning is that investors collectively possess some information that managers do not have. 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 are the ones who put those assets there (e.g., Gao and Liang 2013; Bai, Philippon, and Savov 2016; Edmans, Jayaraman, and Schneemeier 2017; Goldstein and Yang 2019).[6] Thus, the EDGAR implementation is likely to reduce managerial learning to a greater extent in growth firms than in value firms. Consistent with this cross-sectional prediction, we find that growth firms experience a greater reduction in privately informed trading, institutional ownership, and the investment-to-price sensitivity after the EDGAR shock than value firms.

Lastly, we examine the overall effect of the EDGAR implementation on *ex post* firm performance. On the one hand, greater dissemination of corporate disclosures and improved stock market liquidity 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.

[6] The argument is not that the manager is less informed than investors, but only that the manager does not have perfect information about every decision-relevant factor that is related to the firm's growth opportunities.

In summary, our results demonstrate the dual effects of modern information technologies on the real economy. On the one hand, broader information dissemination leads to an increase in stock liquidity, a decrease in return volatility, and an increase in the level of equity financing and corporate investment. These outcomes are consistent with the conventional wisdom that guides regulators in promoting broader and more timely information dissemination. On the other hand, greater dissemination of corporate disclosures crowds out private information acquisition and reduces managerial learning from prices. This crowding-out effect, while often overlooked, is particularly pronounced in growth firms. Our findings suggest that it is important to consider this tradeoff between financing and learning when evaluating the real effects of modern information technologies. More generally, our paper provides evidence that investors' costs of accessing firm disclosures have important implications for corporate investment.

It is worth noting that 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.[7] Thus, we do not claim that the EDGAR implementation represents a clean shock to information dissemination while holding constant the information being disclosed. 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 develops a stylized model that illustrates the theoretical underpinnings of the investment-to-price sensitivity framework. Section 5 presents the

[7] Empirically, Chang, Ljungqvist, and Tseng (2020) find no evidence of changes in firms' disclosure quality around EDGAR inclusion.

main analysis on corporate investment. Section 6 delves into the underlying mechanisms that explain the main results. Section 7 provides some additional analyses. Section 8 concludes and discusses some directions for future research.

2. Related Literature

Our paper makes contributions to three 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)). 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. Using the EDAGR implementation setting, we demonstrate that a reduction in the costs of accessing disclosures influences firms' real decisions due to its effects on equity financing and managerial learning. Our findings highlight the importance of considering information dissemination beyond information production when examining the real effects of corporate disclosures.

Second, our paper contributes to the literature assessing how the costs of monitoring for, 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)). Gao and Huang (2020) and Chang, Ljungqvist, and Tseng (2020) provide evidence that the EDGAR implementation leads to an increase in information production by individual investors and sell-side analysts, and thus a higher stock pricing efficiency. 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. We build on their work and provide evidence suggesting that the EDGAR implementation decreases the amount of information in prices that is new to managers (i.e., revelatory price efficiency). Importantly, we show the real effects of the EDGAR implementation.

Third, our paper extends the literature on the real effects of the financial markets (see reviews in Bond, Edmans, and Goldstein (2012) and Goldstein and Yang (2017)). A growing number of studies in this area rely on the investment-to-price sensitivity framework to draw inferences on managerial learning (e.g., 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; Lin, Liu, and Sun 2019). Most related to our work is Jayaraman and Wu (2019) who find a reduction in a firm's investment-to-price sensitivity after the firm increases segment disclosures. Their results present evidence of reduced managerial learning after an increase in the level of disclosures. A fundamental difference between their work and ours is that they abstract away from investors' costs of accessing disclosures. In contrast, we provide direct evidence on the implications of these costs on corporate investment decisions.

3. Institutional Setting, Sample, and Empirical Specification

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 can either physically visit one of the reference rooms or subscribe to commercial data vendors for a

[8] See "S.E.C. Data: Difficult Hunt" by the *New York Times* (May 19, 1982).

nontrivial fee.[9] This restricted and delayed access to firm disclosures likely creates information asymmetries among investors even though these SEC filings are deemed to be "public."

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 electronically through the EDGAR system after the respective implementation date. 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.[10] The detailed implementation dates for the ten groups are tabulated in Appendix A.

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), intraday transaction data from NYSE Trade and Quote (TAQ), and data on institutional ownership from Thomson Reuters. Following prior research (e.g., Chen, Goldstein,

[9] Chang, Ljungqvist, and Tseng (2020) 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.

[10] 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.

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.

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. $Q_{i,t}$ 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*.

γ_1 is the diff-in-diff estimator and 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 allow them to tap into new investment opportunities. Thus, we predict a positive γ_1.

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; Gormley and Matsa 2016; Gao and Huang 2020). Hence, we run all our regressions without and with controlling for time-varying firm characteristics. We cluster standard errors by firm given multiple quarterly observations for each firm (Petersen 2009).

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:

$$
\begin{aligned}
INVESTMENT_{i,t+1} & \\
&= \alpha_t + \eta_i + \gamma_1 EDGAR_{i,t} + \gamma_2 Q_{i,t} + \gamma_3 CF_{i,t} + \gamma_4 SIZE_{i,t} + \gamma_5 Q_{i,t} \times EDGAR_{i,t} \\
&+ \gamma_6 CF_{i,t} \times EDGAR_{i,t} + \gamma_7 SIZE_{i,t} \times EDGAR_{i,t} + \varepsilon_{i,t+1}
\end{aligned}
\tag{2}
$$

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. To clarify this idea, we develop a stylized model in the next section to highlight the basic mechanism.

4. 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 $\frac{1}{\mu_\theta}$. 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 $\varepsilon_M \sim N(0, \frac{1}{\mu_M})$. Given her information and using Bayesian updating, the firm's manager will optimally set the level of capital K_0 at: $K_0 = E(\theta|prior, M) = \frac{\mu_M}{\mu_\theta + \mu_M} M$.

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 $\varepsilon_{M'} \sim N(0, \frac{1}{\mu_{M'}})$. 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 $\varepsilon_N \sim N(0, \frac{1}{\mu_N})$. 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 one 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., $P_t = E\ (\theta|\text{Market Maker's Information at } t)$. More specifically, $P_1 = E(\theta|prior, M', N) = \frac{\mu_N}{\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}} N + \frac{\frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}}{\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}} M'$.

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: $K_1 = E(\theta|prior, M, N) = \frac{\mu_N}{\mu_\theta + \mu_N + \mu_M} N + \frac{\mu_M}{\mu_\theta + \mu_N + \mu_M} M$. 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: $I_1 = \frac{\mu_N}{\mu_\theta + \mu_N + \mu_M} N + \frac{\mu_M}{\mu_\theta + \mu_N + \mu_M} M - \frac{\mu_M}{\mu_\theta + \mu_M} M = \frac{\mu_N}{\mu_\theta + \mu_N + \mu_M} \left(N - \frac{\mu_M}{\mu_\theta + \mu_M} M \right)$.

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: $\frac{dI_1}{dP_1} = \frac{\mu_N}{\mu_\theta+\mu_N+\mu_M}\left(\frac{dN}{dP_1} - \frac{\mu_M}{\mu_\theta+\mu_M}\frac{dM}{dP_1}\right) = \frac{\mu_N}{\mu_\theta+\mu_N+\mu_M}\left(\gamma_N - \frac{\mu_M}{\mu_\theta+\mu_M}\gamma_M\right)$.

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: $\frac{dI_1}{dP_1} = \frac{1}{Var(P_1)}\frac{\mu_N}{\mu_\theta+\mu_N+\mu_M}\left(Cov(P_1,N) - \frac{\mu_M}{\mu_\theta+\mu_M}Cov(P_1,M)\right)$. Given the model structure, we can derive expressions for $Var(P_1)$, $Cov(P_1,N)$ and $Cov(P_1,M)$ (see the detailed derivations in Appendix B). Substituting these expressions and after some algebra, we get: $\frac{dI_1}{dP_1} = \frac{\mu_N}{\left[\mu_N+\frac{\mu_M \cdot \mu_{M'}}{\mu_M+\mu_{M'}}\right]}\frac{\mu_\theta}{\mu_\theta+\mu_M}$.

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 (μ_N); (2) is decreasing in the precision of the information in the price that is already known to the manager ($\mu_{M'}$); and (3) is decreasing in the precision of managerial information (μ_M).

The intuition behind these results goes as follows: Two types of information affect the price, one is new to the manager, and one 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; Chang, Ljungqvist, and Tseng 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).[11] 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). To answer this question, we rely on two measures based on structural market microstructure models to assess the equilibrium level of private information in prices. Private information gets incorporated into price via investors' trading

[11] 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.

activities. Almost by definition, this information gets discovered only via the price, and thus is likely to be new to managers. A decrease in privately informed trading after the EDGAR implementation will reduce managerial learning from prices and the investment-to-price sensitivity.

Another implication from the model is that the extent to which the manager can learn from the market depends on the precision of her private information (M in the model). When M is very precise, it is less likely that the EDGAR implementation will affect her investment decisions through the learning channel. We expect the precision of M to be relatively high for assets in place and relatively low for growth options. Therefore, if the EDGAR implementation affects the investment-to-price sensitivity through the managerial learning channel, we should observe a stronger effect in growth firms than in value firms.

5. Main Analysis

5.1.Summary Statistics

Table 1 reports the summary statistics for all variables used in our 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 (49.4% versus 50.6%). The average and median Tobin's Q are 1.8 and 1.4, respectively.

5.2.Main Results on Corporate Investment

We analyze the effect of the EDGAR implementation on corporate investment by estimating Equations (1) and (2). Table 2 reports the main regression results. In column 1, we only include *EDGAR* as the independent variable. 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 firms on average increase their capital expenditures after the EDGAR implementation.

In column 3 of Table 2, we report the results of the regression model in Equation (2). 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 20% decline 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. Our conjecture is that the EDGAR implementation leads to a reduction in information in prices that is new to managers (which we test in the next section) and thus managers rely more on their internal information.

5.3.Parallel Trends

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).[12] The diff-in-diff approach does not require *ex ante* firm characteristics (e.g., firm size)

[12] Chang, Ljungqvist, and Tseng (2020, 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.

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). In untabulated analysis, we further augment Equation (2) by interacting Q with firm fixed effects to allow the investment-to-price sensitivity to vary across firms. The coefficient on $Q \times EDGAR$ remains significantly negative (p-value<0.05).

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. 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), we plot the dynamic diff-in-diff estimates (along with the 95% confidence intervals) of the effects of the EDGAR implementation on the investment level and the investment-to-price sensitivity in Figures 1 and 2, respectively. Figure 1 shows that the level of investment is not statistically different between the treatment and control groups in the two quarters before the EDGAR implementation. Figure 2 shows a similar pattern of no differential pre-trends for the investment-to-price sensitivity. The estimates in these two figures provide support for the parallel-trends assumption.

Overall, the evidence in Table 2 and Figures 1 and 2 suggests that EDGAR inclusion results in an increase in the level of investment and a decline in the investment-to-price sensitivity. To provide evidence on the underlying mechanisms, we examine the equity financing channel and the managerial learning channel in the next section.

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.

6. Analysis of Mechanisms

6.1.Equity Financing Channel

First, we analyze the equity financing channel through which the EDGAR implementation affects the level of corporate investment. We estimate the regression model in Equation (3):

$$DEPVAR_{i,t} = \alpha_t + \eta_i + \beta_1 EDGAR_{i,t} + \beta_2 SIZE_{i,t-1} + \beta_3 PRC\_INV_{i,t-1} + \varepsilon_{i,t} \tag{3}$$

where $DEPVAR_{i,t}$ represents the bid-ask spread estimator (*ILLIQUID*) derived from daily high and low prices following Corwin and Schultz (2012), idiosyncratic return volatility (*IVOL*) based on the market model, and the amount of equity issuance (*EQUITY*).

The high-low spread estimator (*ILLIQUID*) captures transitory volatility at the daily level and closely approximates the cost of immediacy.[13] A higher *ILLIQUID* indicates a higher level of stock illiquidity. Corwin and Schultz (2012) show that it generally outperforms other low-frequency estimators and works particularly well in the 1993–1996 period when the minimum tick was one-eighth. The idiosyncratic return volatility (*IVOL*) reflects information asymmetry between firm managers and the market in a framework in which the total uncertainty about a firm is decomposed into market-wide and firm-specific components (Dierkens 1991; Moeller, Schlingermann, and Stulz 2007; Kim, Li, Pan, and Zuo 2013).[14]

$SIZE_{i,t-1}$ 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.

---

[13] The cost (or price) of immediacy is the return that dealers must expect to earn in order to provide liquidity promptly and sufficiently (e.g., Dick-Nielsen and Rossi 2019).

[14] Our inferences remain unchanged with alternative measures of illiquidity (e.g., Amihud 2002) or return volatility (e.g., total return volatility or idiosyncratic return volatility based on the Fama-French (1993) three-factor model).

Table 3 reports the regression results. We include only *EDGAR* as the independent variable in the odd columns and add firm size (*SIZE*) and the inverse of stock price (*PRC_INV*) as controls in the even columns. In columns 1 and 2 of Table 3, the coefficient on *EDGAR* is significantly negative at the 5% level, suggesting an improvement in a firm's stock liquidity after the EDGAR shock. The coefficient of -0.278 in column 1 translates into a 16% reduction (relative to the sample mean) in illiquidity on average. In columns 3 and 4 of Table 3, the coefficient on *EDGAR* is significantly negative at the 1% level, suggesting that a firm's idiosyncratic return volatility decreases by 0.128 percentage points after it becomes an EDGAR filer.

Next, we examine the effect of the EDGAR shock on the amount of equity financing firms obtain. In columns 5 and 6 of Table 3, 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 5 suggests an increase in equity financing by 0.294% of total assets each quarter on average.

Collectively, Table 3 provides evidence supporting the equity financing channel: the EDGAR shock leads to an increase in stock market liquidity, a reduction in stock return volatility, and an increase in equity financing.[15]

6.2.Managerial Learning Channel

6.2.1. 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

[15] In untabulated analysis, we find no evidence that the EDGAR implementation affects the amount of debt financing.

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 it is included in the EDGAR system.

In columns 1 and 2 of Table 4, Panel A, we analyze the effect of the EDGAR shock on institutional ownership (*INSTOWN*). 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. 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 (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 investor 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 investor ownership.

Together, the results in Panel A of Table 4 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 less-sophisticated retail investors than to more-sophisticated institutional investors. By making a firm's disclosures more readily available to retail investors, the EDGAR system 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 section.

6.2.2. Privately Informed Trading

We use as the dependent variable in Equation (3) two measures of private information based on structural market microstructure models. 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 (Easly, 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 4. The sample size is reduced for these two measures because both rely on intraday transactions 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).[16] 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 a 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.

6.2.3. Growth Firms versus Value Firms

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. To perform this test, we divide the full sample of firms into these two types of firms based on the market-to-book ratios in 1992 (i.e., the last year

[16] We thank Edwin Hu and Daniel Taylor for providing us with the *GPIN* and *LAMBDA* measures, respectively.

prior to the EDGAR implementation). *GROWTH_FIRM (VALUE_FIRM)* is an indicator that equals one if a firm's market-to-book ratio in 1992 is above (below) the median, and zero otherwise.

In Panel A of Table 5, we replace *EDGAR* in Equation (3) 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 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 A suggest that the negative effects of the EDGAR shock on privately informed trading and institutional ownership are concentrated in growth firms.[17]

In Panel B of Table 5, we repeat the regression on the investment-to-price sensitivity as specified in Equation (2) by replacing *Q×EDGAR* with its interactions with *GROWTH_FIRM* and *VALUE_FIRM*. In column 1, we repeat our previous analysis in Table 2 for this restricted sample (requiring the availability of the market-to-book ratio in 1992) and the coefficient on *Q×EDGAR* remains significantly negative at the 1% level. In column 2, the coefficient on the interaction term *Q×EDGAR×GROWTH_FIRM* is significantly negative at the 1% level, while the coefficient on *Q×EDGAR×VALUE_FIRM* is statistically insignificant. The difference between these two coefficients is significant at the 1% level. Overall, 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.

In Panel C of Table 5, we repeat the analysis on the equity financing channel and the level of investment by replacing *EDGAR* with its interactions with *GROWTH_FIRM* and *VALUE_FIRM*. We find that the observed EDGAR effects on stock liquidity, return volatility, equity financing,

[17] Our inferences are unchanged when we include the (endogenous) firm-level controls as in Table 4.

and corporate investment are concentrated in value firms. We view these results as descriptive and consistent with the Myers and Majluf (1984) framework in which information asymmetry about assets in place (not growth options) causes adverse selection problems.

7. Additional Analysis

7.1.Firm Performance

In this section, we investigate the effects of the EDGAR implementation on *ex post* firm performance. We perform two sets of tests as follows. First, in Panel A of Table 6, we rerun the regression model in Equation (3) by replacing the dependent variable with the return on equity (*ROE*), 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 5% level or better in all six 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, 3, and 5 translate into an increase of 9% in *ROE*, 12% in *ROA*, and 20% in *ΔSALES* (relative to their sample means), respectively.

Second, we rerun the same regression but replace *EDGAR* with *EDGAR×GROWTH_FIRM* and *EDGAR×VALUE_FIRM* in Panel B of Table 6. The coefficient on *EDGAR×VALUE_FIRM* is significantly positive at the 1% level, while that on *EDGAR×GROWTH_FIRM* is negative and 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.

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 6. The coefficient on *EDGAR×HIGH_GROWTH_FIRM* is significantly negative in all columns, while the coefficient on *EDGAR×LOW_GROWTH_FIRM* is positive and 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.[18]

Collectively, the results in Table 6 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.

7.2.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 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).[19] Table 7 reports the results for this analysis. Both the magnitude and statistical significance of the coefficients on *Q* and *EDGAR×Q* are quite similar to those reported in Table 2.

[18] We also repeat our analysis in Table 5 for high-growth and low-growth firms and do not find evidence that the EDGAR implementation differentially reduces privately informed trading or the investment-to-price sensitivity 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.

[19] 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.

Second, we repeat our analysis after redefining the *EDGAR* indicator for 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.[20] Table 8 presents the results and our inferences remain largely unchanged.

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 but a 20% decrease in the investment-to-price sensitivity. The increased level of investment is consistent with the conventional wisdom that broader information dissemination leads to an increase in stock liquidity, a decrease in return volatility, and an increase in the level of equity financing. The decreased investment-to-price sensitivity suggests that greater dissemination of corporate disclosures can crowd out private information acquisition and reduce managerial learning from prices. We provide evidence of improved equity financing and reduced managerial learning after the EDGAR implementation. 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.

[20] See "Plan Opens More Data to Public" by the *New York Times* (October 22, 1993).

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.

References

Akins, B.K., Ng, J., Verdi, R.S., 2012. Investor competition over information and the pricing of information asymmetry. *The Accounting Review* 87 (1), 35–58.

Alti, A., 2003. How sensitive is investment to cash flow when financing is frictionless? *Journal of Finance* 58 (2), 707–722.

Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets* 5 (1), 31–56.

Angrist, J.D., Pischke, J.S., 2009. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Armstrong, C.S., Core, J.E., Taylor, D.J., Verrecchia, R.E., 2011. When does information asymmetry affect the cost of capital? *Journal of Accounting Research* 49 (1), 1–40.

Bai, J., Philippon, T., Savov, A., 2016. Have financial markets become more informative? *Journal of Financial Economics* 122 (3), 625–654.

Bakke, T.E., Whited, T.M., 2010. Which firms follow the market? An analysis of corporate investment decisions. *Review of Financial Studies* 23 (5), 1941–1980.

Blankespoor, E., deHaan, E., Marinovic, I., 2020. Disclosure processing costs, investors' information choice, and equity market outcomes: A review. *Journal of Accounting and Economics,* Forthcoming.

Bond, P., Edmans, A., Goldstein, I., 2012. The real effects of financial markets. *Annual Review of Financial Economics* 4, 339–360.

Bushee, B. 1998. The influence of institutional investors on myopic R&D investment behavior. *The Accounting Review* 73 (3), 305–333.

Chang, Y., Ljungqvist, A., Tseng, K., 2020. Do corporate disclosures constrain strategic analyst behavior? *CEPR Discussion Paper* No. DP14678.

Chen, Q., Goldstein, I., Jiang, W., 2007. Price informativeness and investment sensitivity to stock price. *Review of Financial Studies* 20 (3), 619–650.

Corwin, S.A., Schultz, P., 2012. A simple way to estimate bid-ask spreads from daily high and low prices. *Journal of Finance* 67 (2), 719–760.

Dessaint, O., Foucault, T., Frésard, L., Matray, A., 2019. Noisy stock prices and corporate investment. *Review of Financial Studies* 32 (7), 2625–2672.

Diamond, D.W., Verrecchia, R.E., 1991. Disclosure, liquidity, and the cost of capital. *Journal of Finance* 46 (4), 1325–1359.

Dick-Nielsen, J., Rossi, M., 2019. The cost of immediacy for corporate bonds. *Review of Financial Studies* 32 (1), 1–41.

Dierkens, N., 1991. Information asymmetry and equity issues. *Journal of Financial and Quantitative Analysis* 26 (2), 181–200.

Duarte, J., Hu, E., Young, L., 2020. A comparison of some structural models of private information arrival. *Journal of Financial Economics* 135 (3), 795–815.

Dugast, J., Foucault, T., 2018. Data abundance and asset price informativeness. *Journal of Financial Economics* 130 (2), 367–391.

Easley, D., Kiefer, N.M., O'Hara, M., Paperman, J.B., 1996. Liquidity, information, and infrequently traded stocks. *Journal of Finance* 51(4), 1405–1436.

Easley, D., O'Hara, M., 1987. Price, trade size, and information in securities markets. *Journal of Financial Economics* 19 (1), 69–90.

Edmans, A., Jayaraman, S., Schneemeier, J., 2017. The source of information in prices and investment-price sensitivity. *Journal of Financial Economics* 126 (1), 74–96.

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33 (1), 3–56.

Fama, E.F., Miller, M.H., 1972. *The Theory of Finance*. New York: Holt, Rinehart, and Winston.

Foucault, T., Frésard, L., 2012. Cross-listing, investment sensitivity to stock price, and the learning hypothesis. *Review of Financial Studies* 25 (11), 3305–3350.

Foucault, T., Frésard, L., 2014. Learning from peers' stock prices and corporate investment. *Journal of Financial Economics* 111 (3), 554–577.

Gao, M., Huang, J., 2020. Informing the market: The effect of modern information technologies on information production. *Review of Financial Studies* 33 (4), 1367–1411.

Gao, P., Liang, P.J., 2013. Informational feedback, adverse selection, and optimal disclosure policy. *Journal of Accounting Research* 51 (5), 1133–1158.

Glosten, L.R., Milgrom, P.R., 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics* 14 (1), 71–100.

Goldstein, I., Jiang, W., Karolyi, G.A., 2019. To FinTech and beyond. *Review of Financial Studies* 32 (5), 1647–1661.

Goldstein, I., Yang, L., 2015. Information diversity and complementarities in trading and information acquisition. *Journal of Finance* 70 (4), 1723–1765.

Goldstein, I., Yang, L., 2017. Information disclosure in financial markets. *Annual Review of Financial Economics* 9, 101–125.

Goldstein, I., Yang, L., 2019. Good disclosure, bad disclosure. *Journal of Financial Economics* 131 (1), 118-138.

Gormley, T.A., Matsa, D.A., 2016. Playing it safe? Managerial preferences, risk, and agency conflicts. *Journal of Financial Economics* 122 (3), 431–455.

Grossman, S.J., Stiglitz, J.E., 1980. On the impossibility of informationally efficient markets. *American Economic Review* 70 (3), 393–408.

Hayek, F.A., 1945. The use of knowledge in society. *American Economic Review* 35 (4), 519–530.

Heitzman, S., Huang, M., 2019. Internal information quality and the sensitivity of investment to market prices and accounting profits. *Contemporary Accounting Research* 36 (3), 1699–1723.

Hirshleifer, J., 1971. The private and social value of information and the reward to inventive activity. *American Economic Review* 61 (4), 561–574.

Holmström, B., 1979. Moral hazard and observability. *Bell Journal of Economics* 10 (1), 74–91.

Jayaraman, S., Wu, J.S., 2019. Is silence golden? Real effects of mandatory disclosure. *Review of Financial Studies* 32 (6), 2225–2259.

Jayaraman, S., Wu, J.S., 2020. Should I stay or should I grow? Using voluntary disclosure to elicit market feedback. *Review of Financial Studies*, Forthcoming.

Jensen, M., Meckling, W.H., 1976. Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics* 3 (4), 305–360.

Kanodia, C., Sapra, H., 2016. A real effects perspective to accounting measurement and disclosure: Implications and insights for future research. *Journal of Accounting Research* 54 (2), 623–676.

Ke, B., Petroni, K., 2004. How informed are actively trading institutional investors? Evidence from their trading behavior before a break in a string of consecutive earnings increases. *Journal of Accounting Research* 42 (5), 895–927.

Ke, B., Ramalingegowda, S., 2005. Do institutional investors exploit the post-earnings announcement drift? *Journal of Accounting and Economics* 39 (1), 25–53.

Kim, Y., Li, S., Pan, C., Zuo, L., 2013. The role of accounting conservatism in the equity market: Evidence from seasoned equity offerings. *The Accounting Review* 88 (4), 1327–1356.

Kothari, S., So, E.C., Verdi, R., 2016. Analysts' forecasts and asset pricing: A survey. *Annual Review of Financial Economics* 8, 197–219.

Kurlat, P., Veldkamp, L., 2015. Should we regulate financial information? *Journal of Economic Theory* 158 (B), 697–720.

Kyle, A.S., 1985. Continuous auctions and insider trading. *Econometrica* 53 (6), 1315–1335.

Lee, C.M., So, E.C., 2015. Alphanomics: The informational underpinnings of market efficiency. *Foundations and Trends® in Accounting* 9 (2–3), 59–258.

Leuz, C., Wysocki, P.D., 2016. The economics of disclosure and financial reporting regulation: Evidence and suggestions for future research. *Journal of Accounting Research* 54 (2), 525–622.

Lin, T., Liu, Q., Sun, B., 2019. Contractual managerial incentives with stock price feedback. *American Economic Review* 109 (7), 2446–2468.

Luo, Y., 2005. Do insiders learn from outsiders? Evidence from mergers and acquisitions. *Journal of Finance* 60 (4), 1951–1982.

Madhavan, A., Richardson, M., Roomans, M., 1997. Why do security prices change? A transaction-level analysis of NYSE stocks. *Review of Financial Studies* 10 (4), 1035–1064.

Merton, R.C., 1987. A simple model of capital market equilibrium with incomplete information. *Journal of Finance* 42 (3), 483–510.

Moeller, S.B., Schlingermann, F.P., Stulz, R.M., 2007. How do diversity of opinion and information asymmetry affect acquirer returns? *Review of Financial Studies* 20 (6), 2047–2078.

Morris, S., Shin, H.S., 2002. Social value of public information. *American Economic Review* 92 (5), 1521–1534.

Myers, S.C., Majluf, N.S., 1984. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics* 13 (2), 187–221.

Petersen, M.A., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies* 22 (1), 435–480.

Roychowdhury, S., Shroff, N., Verdi, R.S., 2019. The effects of financial reporting and disclosure on corporate investment: A review. *Journal of Accounting and Economics* 68 (2–3), 1–27.

Watts, R.L., Zimmerman, J.L., 1986. *Positive Accounting Theory*. New Jersey: Prentice-Hall Inc.

Zuo, L., 2016. The informational feedback effect of stock prices on management forecasts. *Journal of Accounting and Economics* 61 (2–3), 391–413.

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 implementation dates for the ten phase-in groups (SEC Release No. 33-6977, SEC issued Release No. 33-7122).

Appendix B: Derivations of $\boldsymbol{Cov(P_1, N)}$, $\boldsymbol{Cov(P_1, M)}$, and $\boldsymbol{Var(P_1)}$

$$Cov(P_1, N) = \frac{\mu_N}{\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}} Var(N) + \frac{\frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}}{\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}} Cov(N, M')$$

$$= \frac{\mu_N}{\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}} \left(\frac{1}{\mu_\theta} + \frac{1}{\mu_N}\right) + \frac{\frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}}{\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}} \frac{1}{\mu_\theta}$$

$$= \left(\frac{\mu_N + \mu_\theta}{\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}} + \frac{\frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}}{\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}}\right) \frac{1}{\mu_\theta} = \frac{1}{\mu_\theta}.$$

$$Cov(P_1, M) = \frac{\mu_N}{\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}} Cov(N, M) + \frac{\frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}}{\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}} Cov(M, M')$$

$$= \frac{\mu_N}{\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}} \frac{1}{\mu_\theta} + \frac{\frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}}{\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}} \left(\frac{\mu_\theta + \mu_M}{\mu_\theta \mu_M}\right)$$

$$= \frac{1}{\mu_\theta} \left(\frac{\mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}} \frac{\mu_\theta \cdot \mu_M}{\mu_M}}{\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}}\right).$$

$$Var(P_1) = \left(\frac{\mu_N}{\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}}\right)^2 \left(\frac{1}{\mu_\theta} + \frac{1}{\mu_N}\right)$$

$$+ \left(\frac{\frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}}{\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}}\right)^2 \left(\frac{1}{\mu_\theta} + \frac{1}{\mu_M} + \frac{1}{\mu_{M'}}\right)$$

$$+2\left(\frac{\mu_N}{\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}}\right)\left(\frac{\frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}}{\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}}\right)\frac{1}{\mu_\theta}$$

$$= \frac{\mu_N \frac{\mu_\theta + \mu_N}{\mu_\theta} + \left(\frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}\right)^2 \left(\frac{1}{\mu_\theta} + \frac{1}{\mu_M} + \frac{1}{\mu_{M'}}\right) + 2\frac{\mu_N}{\mu_\theta} \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}}{\left(\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}\right)^2}$$

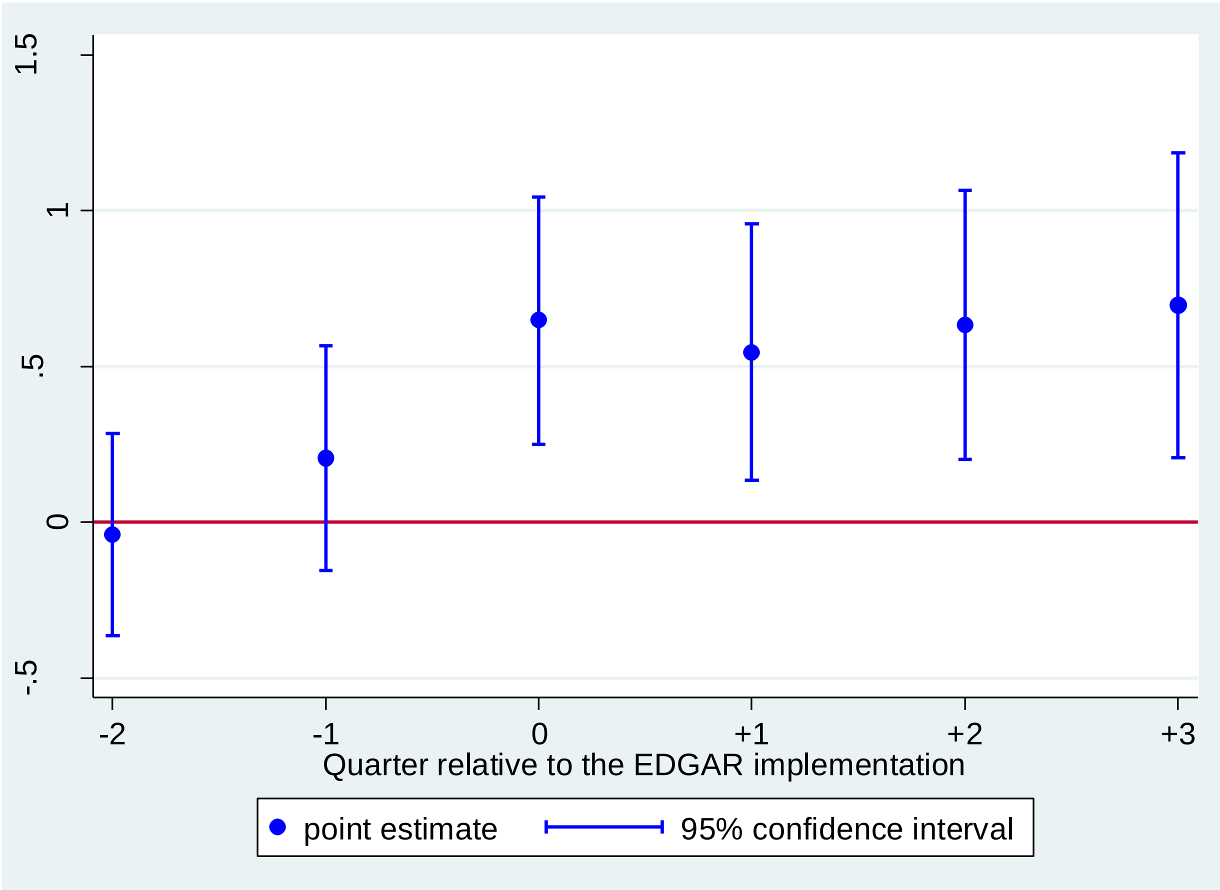
$$= \frac{\frac{1}{\mu_\theta}\left[\mu_N(\mu_\theta + \mu_N) + \left(\frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}\right)\left(\left(\frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}\right) + \mu_\theta + \mu_N\right) + \mu_N \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}\right]}{\left(\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}\right)^2}$$

$$= \frac{1}{\mu_\theta} \frac{\mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}}{\left(\mu_\theta + \mu_N + \frac{\mu_M \cdot \mu_{M'}}{\mu_M + \mu_{M'}}\right)}.$$

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 in the next quarter scaled by the net property, plant, and equipment (PPENTQ) at the current quarter end. Compustat quarterly data provide year-to-date 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.
ILLIQUID	=	The bid-ask spread estimated from daily high and low prices following Corwin and Schultz (2012). Specifically, it is the estimate of a stock's bid-ask spread as a function of the high-to-low price ratio for a single two-day period and the high-to-low ratios for two consecutive single days. It is expressed in percentage points.
IVOL	=	The standard deviation of the residuals of the market model estimated using the daily stock returns over the quarter. It is expressed in percentage points.
EQUITY	=	Equity issuance (SSTKQ) scaled by lagged total assets (ATQ). It is 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).
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.
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. Market-to-book ratio is defined as the ratio of the market value of a firm's common stock (CSHO×PRCC) to its book value (CEQ). It is set to missing if CEQ is negative.
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.
ROE	=	The ratio of operating income before depreciation (OIBDPQ) to lagged book value of equity (CEQQ), expressed in percentage points. It is set to missing if the lagged CEQQ is negative.
ROA	=	The ratio of operating income before depreciation (OIBDPQ) to lagged book value of total assets (ATQ), expressed in percentage points.
ΔSALES	=	Growth rate in sales (SALEQ) from the same quarter in the previous year to the current quarter, 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: Time Trends of the Investment Level

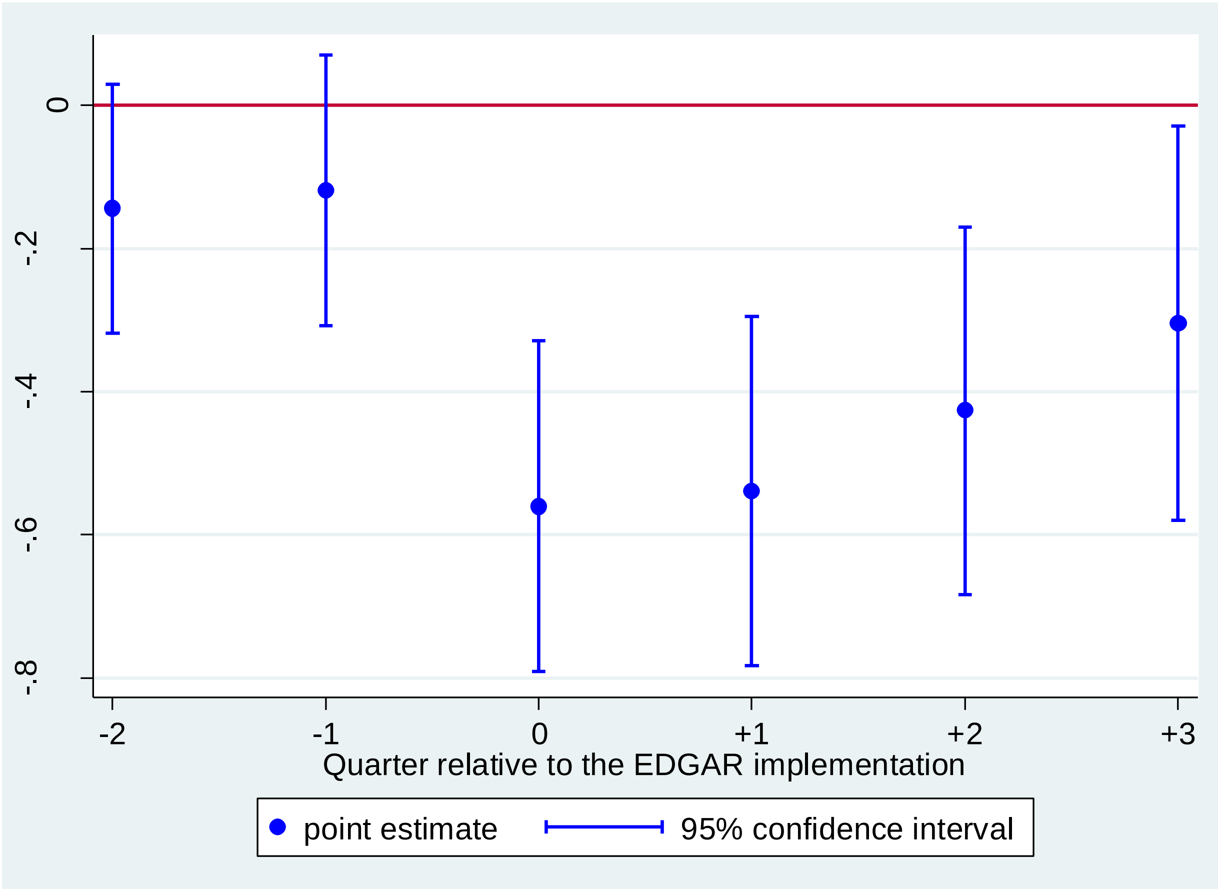


Notes: This figure reports the results from an event-time analysis of the effect of the EDGAR implementation on the level of corporate investment. Specifically, we re-estimate the regression model on the level of investment in column 1 of Table 2 by replacing *EDGAR* with a set of indicators for the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

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

where $EDGAR(-2)_{i,t}$ ($EDGAR(-1)_{i,t}$) is an indicator that equals one if a firm will become a mandatory EDGAR filer in 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. All estimations include firm and year-quarter fixed effects. The standard errors are clustered at the firm level.

Figure 2: Time Trends of the Investment-to-Price Sensitivity



Notes: This figure reports the results from an event-time analysis of the effect of the EDGAR implementation on the investment-to-price sensitivity. Specifically, we re-estimate the regression model on the investment-to-price sensitivity in column 3 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:

$$
\begin{aligned}
INVESTMENT_{i,t+1} &= \alpha_t + \eta_i + \gamma_1 EDGAR_{i,t} + \gamma_2 Q_{i,t} + \gamma_3 CF_{i,t} + \gamma_4 SIZE_{i,t} + \gamma_5 Q_{i,t} \times EDGAR(-2)_{i,t} \\
&+ \gamma_6 Q_{i,t} \times EDGAR(-1)_{i,t} + \gamma_7 Q_{i,t} \times EDGAR(0)_{i,t} + \gamma_8 Q_{i,t} \times EDGAR(+1)_{i,t} \\
&+ \gamma_9 Q_{i,t} \times EDGAR(+2)_{i,t} + \gamma_{10} Q_{i,t} \times EDGAR(+3)_{i,t} + \gamma_{11} Q_{i,t} \times EDGAR(4+)_{i,t} \\
&+ \gamma_{12} CF_{i,t} \times EDGAR_{i,t} + \gamma_{13} SIZE_{i,t} \times EDGAR_{i,t} + \varepsilon_{i,t+1}
\end{aligned}
$$

where $EDGAR(-2)_{i,t}$ ($EDGAR(-1)_{i,t}$) is an indicator that equals one if a firm will become a mandatory EDGAR filer in 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 the interaction between Q and each event quarter indicator as well as their 95% confidence intervals. All estimations include firm and year-quarter fixed effects. 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
ILLIQUID	63,970	1.722	2.637	0.030	0.756	2.481
IVOL	64,610	3.484	2.278	1.900	2.900	4.316
EQUITY	64,335	1.001	5.058	0.000	0.012	0.183
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
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
ROE	63,545	4.349	11.107	1.083	4.764	8.299
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 all variables used in our analysis. 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

Dependent Variable =	*INVESTMENT*		
	(1)	(2)	(3)
EDGAR	**0.613***** **(4.05)**	**0.403***** **(2.84)**	**0.933***** **(3.09)**
Q		1.714*** (18.97)	1.908*** (18.64)
CF		0.178*** (12.94)	0.136*** (7.34)
SIZE		0.354** (2.10)	0.381** (2.23)
Q×EDGAR			**-0.392***** **(-3.90)**
CF×EDGAR			0.081*** (3.35)
SIZE×EDGAR			0.004 (0.08)
Firm FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Observations	66,628	66,628	66,628
Adjusted *R*-squared	0.272	0.302	0.304

Notes: This table reports the regression results on corporate investment. The dependent variable is the quarterly investment made by the firm, defined as capital expenditure in the next quarter scaled by the net property, plant, and equipment at the current quarter end (*INVESTMENT*). *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 3: Equity Financing Channel

Dependent Variable =	*ILLIQUID*		*IVOL*		*EQUITY*	
	(1)	(2)	(3)	(4)	(5)	(6)
EDGAR	**-0.278*****	**-0.257*****	**-0.128*****	**-0.126*****	**0.294*****	**0.253*****
	(-6.90)	**(-7.82)**	**(-3.72)**	**(-4.38)**	**(3.20)**	**(2.83)**
SIZE		-0.117***		-0.126***		-1.999***
		(-3.29)		(-3.83)		(-16.33)
PRC_INV		3.464***		2.647***		-1.214***
		(32.20)		(23.12)		(-11.18)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63,970	63,970	64,610	64,610	64,335	64,335
Adjusted *R*-squared	0.676	0.759	0.660	0.729	0.089	0.107

Notes: This table reports the regression results on the equity financing channel. The dependent variables include the high-low spread estimator (*ILLIQUID*), idiosyncratic return volatility (*IVOL*), 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. 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 4: Managerial Learning Channel

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

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*). *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 5: Growth Firms versus Value Firms

Panel A: Managerial Learning Channel				
Dependent Variable =	*INSTOWN*	*INSTOWN_TRA*	*GPIN*	*LAMBDA*
	(1)	(2)	(3)	(4)
***EDGAR×GROWTH_FIRM* (a)**	**-0.942*****	**-0.824*****	**-4.206****	**-0.018*****
	(-2.73)	**(-4.23)**	**(-2.45)**	**(-4.62)**
***EDGAR×VALUE_FIRM* (b)**	**-0.196**	**-0.055**	**-1.725**	**-0.000**
	(-0.52)	**(-0.29)**	**(-1.25)**	**(-0.09)**
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

Panel B: Investment-to-Price Sensitivity		
Dependent Variable =	*INVESTMENT*	
	(1)	(2)
EDGAR	0.814***	0.334
	(2.67)	(1.00)
Q	1.915***	1.807***
	(18.08)	(16.38)
CF	0.135***	0.134***
	(6.81)	(6.74)
SIZE	0.393**	0.388**
	(2.17)	(2.14)
Q×EDGAR	**-0.342*****	
	(-3.30)	
***Q×EDGAR×GROWTH_FIRM* (a)**		**-0.291*****
		(-2.74)
***Q×EDGAR×VALUE_FIRM* (b)**		**0.153**
		(0.79)
CF×EDGAR	0.080***	0.077***
	(3.13)	(2.99)
SIZE×EDGAR	0.008	0.035
	(0.18)	(0.74)
Test of (a)=(b) (*p*-value)		**<0.001**
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	62,441	62,441
Adjusted *R*-squared	0.304	0.304

Panel C: Equity Financing Channel				
Dependent Variable =	*ILLIQUID*	*IVOL*	*EQUITY*	*INVESTMENT*
	(1)	(2)	(3)	(4)
***EDGAR×GROWTH_FIRM* (a)**	**-0.071**	**-0.028**	**0.052**	**-0.123**
	(-1.43)	**(-0.70)**	**(0.48)**	**(-0.68)**
***EDGAR×VALUE_FIRM* (b)**	**-0.436*** **	**-0.185*** **	**0.490*** **	**1.384*** **
	(-8.42)	**(-4.18)**	**(4.79)**	**(7.74)**
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	60,438	61,059	60,335	62,441
Adjusted R-squared	0.681	0.665	0.090	0.273

Notes: This table reports the regression results for the differential treatment effects in growth firms and value firms. In Panel A, the dependent variables include total institutional ownership (*INSTOWN*), transient institutional ownership (*INSTOWN_TRA*), the probability of informed trading (*GPIN*), and the adverse selection component of the bid-ask spread (*LAMBDA*). In Panel B, the dependent variable is the quarterly investment made by the firm, defined as capital expenditure in the next quarter scaled by the net property, plant, and equipment at the current quarter end (*INVESTMENT*). In Panel C, the dependent variables include the high-low spread estimator (*ILLIQUID*), idiosyncratic return volatility (*IVOL*), the amount of equity issuance (*EQUITY*), and the quarterly investment made by the firm (*INVESTMENT*). *GROWTH_FIRM* (*VALUE_FIRM*) is an indicator that equals one if a firm's market-to-book ratio in 1992 is above (below) 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 6: Firm Performance

Panel A: Baseline Analyses

Dependent Variable =	*ROE*		*ROA*		*ΔSALES*	
	(1)	(2)	(3)	(4)	(5)	(6)
EDGAR	**0.388****	**0.403****	**0.198*****	**0.200*****	**2.878*****	**2.989*****
	(1.97)	**(2.05)**	**(3.07)**	**(3.12)**	**(2.89)**	**(3.01)**
SIZE		0.168		-0.054		2.220*
		(0.57)		(-0.61)		(1.78)
PRC_INV		-2.430***		-0.853***		-9.984***
		(-5.21)		(-8.79)		(-8.35)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63,545	63,545	66,094	66,094	65,477	65,477
Adjusted *R*-squared	0.446	0.449	0.557	0.560	0.179	0.184

Panel B: Growth Firms versus Value Firms

Dependent Variable =	*ROE*		*ROA*		*ΔSALES*	
	(1)	(2)	(3)	(4)	(5)	(6)
EDGAR×GROWTH_FIRM **(a)**	**-0.357**	**-0.341**	**-0.111**	**-0.092**	**-0.172**	**-0.136**
	(-1.40)	**(-1.34)**	**(-1.34)**	**(-1.11)**	**(-0.15)**	**(-0.12)**
EDGAR×VALUE_FIRM **(b)**	**1.067*****	**1.073*****	**0.515*****	**0.509*****	**6.650*****	**6.853*****
	(4.56)	**(4.55)**	**(6.23)**	**(6.18)**	**(5.52)**	**(5.66)**
Test of (a)=(b) (*p*-value)	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**
Controls	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,065	61,065	62,054	62,054	61,461	61,461
Adjusted *R*-squared	0.443	0.446	0.562	0.565	0.177	0.182

Panel C: High versus Low Growth Firms

Dependent Variable =	*ROE*		*ROA*		*ΔSALES*	
	(1)	(2)	(3)	(4)	(5)	(6)
EDGAR×HIGH_GROWTH_FIRM **(a)**	**-1.018*****	**-0.974****	**-0.290****	**-0.257****	**-2.617***	**-2.560***
	(-2.66)	**(-2.53)**	**(-2.29)**	**(-2.03)**	**(-1.75)**	**(-1.73)**
EDGAR×LOW_GROWTH_FIRM **(b)**	**0.295**	**0.276**	**0.069**	**0.071**	**2.271***	**2.254***
	(0.95)	**(0.90)**	**(0.68)**	**(0.71)**	**(1.69)**	**(1.69)**
EDGAR×VALUE_FIRM	1.071***	1.082***	0.516***	0.511***	6.668***	6.892***
	(4.57)	(4.58)	(6.23)	(6.20)	(5.53)	(5.68)
Test of (a)=(b) (*p*-value)	**0.006**	**0.008**	**0.023**	**0.036**	**0.003**	**0.003**
Controls	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,065	61,065	62,054	62,054	61,461	61,461
Adjusted *R*-squared	0.443	0.446	0.562	0.565	0.177	0.182

Notes: This table reports the regression results on firm performance. The dependent variables include the return on equity (*ROE*), 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. *GROWTH_FIRM* (*VALUE_FIRM*) is an indicator that equals one if a firm's market-to-book ratio in 1992 is above (below) the median, and zero otherwise. *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. 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 7: Removal of Transitional Filers

Dependent Variable =	*INVESTMENT*		
	(1)	(2)	(3)
EDGAR	**0.717*****	**0.488*****	**1.073*****
	(4.60)	**(3.32)**	**(3.37)**
Q		1.711***	1.903***
		(18.77)	(18.50)
CF		0.178***	0.136***
		(12.81)	(7.29)
SIZE		0.353**	0.386**
		(2.07)	(2.21)
Q×EDGAR			**-0.388*****
			(-3.82)
CF×EDGAR			0.082***
			(3.38)
SIZE×EDGAR			-0.008
			(-0.16)
Firm FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Observations	64,612	64,612	64,612
Adjusted *R*-squared	0.271	0.301	0.302

Notes: This table reports the regression results on corporate investment after excluding firms assigned to Group CF-01 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, defined as capital expenditure in the next quarter scaled by the net property, plant, and equipment at the current quarter end (*INVESTMENT*). *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 8: Requirement of Free Online Access

Dependent Variable =	*INVESTMENT*		
	(1)	(2)	(3)
EDGAR	**0.803*****	**0.532*****	**1.017*****
	(4.84)	**(3.39)**	**(3.40)**
Q		1.712***	1.900***
		(18.95)	(18.64)
CF		0.177***	0.134***
		(12.93)	(7.33)
SIZE		0.356**	0.375**
		(2.12)	(2.19)
Q×EDGAR			**-0.383*****
			(-3.85)
CF×EDGAR			0.087***
			(3.59)
SIZE×EDGAR			0.006
			(0.14)
Firm FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Observations	66,628	66,628	66,628
Adjusted *R*-squared	0.272	0.302	0.304

Notes: This table reports the regression results on corporate investment after redefining the *EDGAR* indicator for 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, defined as capital expenditure in the next quarter scaled by the net property, plant, and equipment at the current quarter end (*INVESTMENT*). *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.