Causal Effect of Information Costs on Asset Pricing Anomalies

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Abstract

Active investors strive to beat the market by obtaining an information edge, a costly enterprise that reduces their net profits (Grossman and Stiglitz (1980)). Prior research ignores information costs because they are hard to measure. The SEC's EDGAR slashed the costs of acquiring and trading on accounting information. Using the staggered EDGAR introduction, we show that average alphas for 125 accounting anomalies decline substantially; the decline almost entirely explains pre-EDGAR alphas. In contrast, alphas for 80 non-accounting anomalies do not change significantly. We conclude that the information costs are substantial and as important as trading and short sale costs.

Keywords: Information costs, stock anomalies, EDGAR, limits-to-arbitrage

1. Introduction

Traditional asset pricing theories such as the CAPM (Sharpe (1964), Lintner (1965), Mossin (1966)) and APT (Ross (1976)) assume frictionless markets, including costless trading and information gathering. Theoretical contributions by Grossman and Stiglitz (1980) and Verrecchia (1982)) are quick to point out that costly information acquisition, an inevitable reality of financial markets,[1] affects investor decisions and market outcomes. Investors purchase the data, hire analysts to clean and process it, and provide them with necessary hardware and software tools; each of these steps is costly. Nonetheless, most prior studies ignore the information costs and instead focus on the trading costs (e.g., Novy-Marx and Velikov (2015)) or short sale costs (e.g., Chu, Hirshleifer, and Ma (2020)).[2] Consequently, there continues to be a lack of empirical studies that undertake the challenging task of quantifying the costs of acquiring information. This paper fills that gap in the literature by using a quasi-natural experiment—the SEC's staggered implementation of the Electronic Data Gathering, Analysis and Retrieval (EDGAR) system from February 1993 to May 1996—to estimate information costs in the U.S. equity markets.

There are several reasons why the introduction of EDGAR is well-suited for our inquiry. First, EDGAR is an online system that enables companies to report their corporate filings electronically and investors to download them freely from anywhere in the world, and its adoption drastically lowered investors' information acquisition costs. Before EDGAR, a comprehensive analysis of a broad cross-section of stocks was cost-prohibitive or impractical for most investors

[1] Indeed, although recent technological advances lowered information gathering and disseminating costs, a typical hedge fund spent over $1 million on data subscriptions alone in 2019 (Whyte (2020)).
[2] Other notable studies of the effect of regular costs on stock anomalies include Keim and Madhavan (1997), Korajczyk and Sadka (2004), Lesmond, Schill, and Zhou (2004), Frazzini, Israel, and Moskowitz (2018), Patton and Weller (2020) for trading costs, and Geczy, Musto, and Reed (2002) and Drechsler and Drechsler (2014) for short sale costs.

(Chang, Ljungqvist, and Tseng (2021)). An investor could physically visit one of SEC's reference rooms in Washington DC, New York, or Chicago and go through paper financial statements; pursue very costly subscriptions to commercial data vendors' services such as Compustat, Value Line, or Dialog, which were often delayed and contradicted one another (Kern and Morris (1994)), or request companies to mail the filing documents.

Second, most known stock anomalies rely on accounting information. We study a pivotal moment as of which EDGAR made this information convenient and inexpensive to access. Third, the SEC's adoption design allows us to harness the staggered difference-in-difference framework. The SEC adopted EDGAR following a phase-in schedule over three years, randomly assigning each public firm to one of ten implementation phases. This adoption design helps us identify a causal effect of information costs on anomaly profitability, with identification coming from firms entering EDGAR at different times and from anomalies requiring—or not requiring—accounting information. Finally, Grossman and Stiglitz (1980) establish that, in a competitive equilibrium, the drop in trading profitability matches the decrease in information costs. Accordingly, studying anomaly profitability enables us to estimate information costs for the marginal investor.

We analyze a comprehensive set of anomalies documented in Chen and Zimmermann (2020), who replicate most of the known stock return anomalies. Our baseline results are grounded in a panel of long-short portfolio monthly returns for nine implementation stages (the third and fourth stages start on the same date) and 205 asset-pricing anomalies, 125 of which require accounting information and 80 do not. We then estimate the effect of EDGAR introduction on anomaly alphas in a staggered difference-in-difference framework.

EDGAR enables convenient access to firms' accounting information; accordingly, we find that the Fama-French six-factor (the Fama and French (2015) five factors and the Carhart (1997) momentum factor) alphas for the accounting-based anomaly portfolios decline on average by 47 basis points to 62 basis points per month (or 5.7% to 7.4% per year) in response to the EDGAR introduction. The average Fama-French alpha of the accounting anomaly portfolios in the treatment group before the EDGAR implementation is 52.9 basis points per month. Therefore, the 47-62 basis points drop accounts for virtually all of the pre-EDGAR alphas. By contrast, EDGAR has not lowered the costs of gathering other, non-accounting information. Indeed, we find that the non-accounting anomaly alphas have not been affected by the EDGAR introduction. The results are robust to using alternative factor models.

The EDGAR-prompted decline in profitability of accounting anomalies should be more pronounced among the stocks of firms regarding which the information was more difficult to gather in the pre-EDGAR period. We use two empirical proxies for information availability—analyst coverage and market capitalization (e.g., Kelly and Ljungqvist (2012))—to show that, indeed, the accounting anomalies' profitability decline associated with the EDGAR introduction is primarily driven by stocks with low information availability (stocks followed by fewer analysts or stocks with below-median market capitalization)—approximately 70-71 basis points per month, or about 8.5% per year. In contrast, the EDGAR-prompted profitability decline for accounting anomalies for high information availability stocks is statistically indistinguishable from zero.

Splitting each anomaly portfolio into short and long legs reveals that profit attenuation effects are concentrated among the short legs of the accounting anomaly portfolios. This finding is consistent with the results reported by Stambaugh, Yu, and Yuan (2012), who find that the anomalies that they study are concentrated primarily in the short legs. Thus, activity by short-sellers, proxied by short interest, should be more informative than activity by long-only investors, proxied by institutional ownership. Indeed, we find that, as stocks in the short leg of accounting anomalies became more efficiently priced, their short interest declined (as a consequence of fewer opportunities for short sellers), while institutional ownership did not change significantly. We also find that trading activity increased less for stocks in top/bottom portfolios of accounting anomalies than for stocks in top/bottom portfolios of non-accounting anomalies, as the former became less attractive to arbitrageurs.

If the EDGAR introduction made stocks in the top and bottom portfolios of accounting anomalies less mispriced (resulting in lower idiosyncratic volatility), these stocks should feature less information asymmetry and should, therefore, become more liquid (hence exhibiting lower Amihud illiquidity). We confirm these hypotheses in the data. The EDGAR introduction is associated with a decline in stock returns' idiosyncratic volatility. This decline is present for both accounting anomalies and non-accounting anomalies, but it is stronger for accounting anomalies. Similarly, following a general trend in increased liquidity, the stocks' Amihud illiquidity measures declined for both types of anomalies, but liquidity increased more for accounting anomalies.

We conclude the list of our empirical tests with a range of robustness checks, including pre-trends and falsification tests that validate our difference-and-difference analysis. We also confirm that the post-publication effect (McLean and Pontiff (2016)) is not driving our results.

Prior literature documents that limits-to-arbitrage such as noise trader risk, trading costs, and short sale costs partially explain anomaly returns, but hardly any study examines the effect of information acquisition costs *per se* on anomaly returns.[3] However, investors incur the costs of acquiring information even before they pay transaction or short sale costs—they need first to

[3] For instance, Geczy, Musto, and Reed (2002) argue that stock borrowing costs explain little of anomaly alphas. In contrast, Chu, Hirshleifer, and Ma (2020) rely on the Reg-SHO pilot program to document that relaxed short sale constraints reduce abnormal returns on 11 anomaly portfolios by 72 basis points per month. Novy-Marx and Velikov (2015) use bid-ask spreads from TAQ to show that the average trading costs range from 20 to 57 basis points per month for the mid-turnover anomalies. In contrast, Frazzini, Israel, and Moskowitz (2018) argue that institutional trading costs are much smaller than those implied by the TAQ data.

identify which stocks to buy or sell before they trade. To our knowledge, we are the first to quantify information acquisition costs and show that the costs can be as high as 42-49 basis points per month, explaining virtually all of the accounting anomalies' pre-EDGAR alphas.[4] Overall, our results suggest that information costs are large.

Our results remain highly relevant for today's markets. Indeed, while utilizing accounting information in active portfolio management was innovative in the mid-1990s, it became quickly commoditized post-EDGAR, reducing its alpha-generating ability. In response, hedge funds and other active managers expanded into new types of data ("alternative data"). Such data are presently expensive and hard to process, a circumstance similar to the status of accounting information pre-EDGAR. Thus, the same principles we uncovered for circumstances surrounding the EDGAR introduction likely apply to these data.

This paper contributes to three strands of literature. First, if contributes to the information costs and market outcomes literature. Merton (1987) and Shapiro (2002) point out that costly information constraints compel investors to only trade the securities regarding which they possess adequate information and show how these constraints affect the general equilibrium process and outcomes. Grossman and Stiglitz (1980) show that reaching perfect market efficiency is elusive because information is costly to collect. Easley and O'Hara (2004) argue that private information presents a systematic risk, prompting uninformed investors to demand compensation for bearing such risk. Our paper contributes to this literature by providing a clean-cut estimation of information acquisition costs in the context of the U.S. equity markets.

[4] Lower costs attracted new arbitrageurs and thus increased the capital pool involved in correcting mispricing caused by accounting anomalies. As a result, the annual alphas associated with trading on such anomalies that require EDGAR information decreased by 6-7%. In the Grossman and Stiglitz (1980) model, this decline in profitability would be attributed solely to the lower information costs.

Second, we also contribute to the stock anomaly literature by identifying the causal effect of information constraints on anomaly returns. Only a few papers study how limits to arbitrage affect anomalies using exogenous shocks to address the endogeneity (e.g., Chu, Hirshleifer, and Ma (2020)). However, unlike our study, such papers do not explore costly information constraints as limits to arbitrage on anomaly returns. McLean and Pontiff (2016) document that the portfolio alphas decline by 58% on average after publication. Whereas they argue that investors learn about anomalies from academic research, we point out that even investors who discover anomalies before academics do face substantial information costs of computing the anomaly signals.

Finally, a strand of literature focuses on the effect of the EDGAR system on financial markets. Gao and Huang (2020) were the first to apply the staggered EDGAR implementation and show that internet dissemination of information prompts corporate outsiders to produce more information. The EDGAR adoption also improves equity financing (Goldstein, Yang, and Zuo (2020)), reduces the information asymmetry between managers and investors (Gomez (2020)), reduces investor disagreement, and mitigates crash risk, especially among stocks with binding short sale constraints and high investor optimism (Chang *et al*. (2022)). Our paper is the first to study how the EDGAR implementation affects the anomaly portfolio returns and to estimate the costs of acquiring information investors bear in the absence of readily accessible accounting information.

2. Implementation of the EDGAR system

A. Costs of Information Acquisition before EDGAR

Prior to the EDGAR adoption in the mid-1990s, the costs of acquiring the information contained in corporate filings were prohibitively large. Investors were mostly limited to three options. The first option was to visit one of the reference rooms in Washington DC, New York, or Chicago where the SEC kept the paper financial statements. The second option was to subscribe to the commercial data vendors' services such as Compustat, Disclosure, Value Line, or Dialog. Lastly, current shareholders could request that the companies mail their filing documents to them.

Anecdotal evidence confirms that the first option was costly and unreliable. Investors had to be physically present in one of the SEC's reference rooms and make a painstaking effort to acquire information on the corporate filings. Occasionally, investors could not even access the information they needed because some of the paper files in the SEC's reference rooms were lost.[5]

The second option was also costly because the pre-EDGAR data aggregators charged high fees. A petition filed to the SEC and the U.S. House of Representatives in 1992 documents the related complaints. The petition demands free public access to corporate filings, pointing out that the Compustat CD-ROM database with historical filings for just 7,200 companies cost $18,000 (Love (1992)).[6] Depending on the coverage, annual subscription fees ranged between $5,000 and $50,000.[7] Value Line Database cost $1,700 per quarter and covered only 1,650 companies. Mead Data Central was only available for a considerable fee that consisted of a $125 monthly fixed fee, a $39 hourly connection fee, and a search fee ranging from $6 to $51 per search.[8]

[5] A *Wall Street Journal* article reports in 1991 that "…nowadays the SEC is being hit by a tidal wave of paper, receiving some 700,000 paper filings every year, amounting to about five million pieces of paper. Those documents are warehoused in the SEC's crowded public reference room, where investors, journalists and financial research organizations routinely comb through stacks of file folders in search of hot documents – and don't always find them."
[6] According to Love (1992), the CD-ROM was called "COMPUSTAT PC Plus." A less expensive product, "COMPUSTAT Corporate Text," was available for $9,000, but was limited in its coverage to only 3,200 firms.
[7] SEC: Oversight of the Edgar System (March 14, 1985), pp. 51.
[8] The petition also reveals that Dialog charged $84 per hour on top of a $1 per page search fee. Compact Disclosure was another popular commercial database at the time. Richards (1988) documents that Compact Disclosure had quarterly updated financial and management information on 10,150 public companies, and cost around $4,500 per year for commercial institutions. However, Richards (1988) notes that Compact Disclosure's access software had technical issues retrieving time-series data, and was missing information on brokerage houses, foreign companies, and microcap stocks with less than $5 million in assets.

Aside from high fees, Compustat suffered from production lag and inaccuracy, which also pushed up the costs of acquiring accurate financial information. D'Souza, Ramesh, and Shen (2010) find that Compustat had an average dissemination lag of 24.7 weekdays prior to the EDGAR (that lag dropped by almost 50% once EDGAR was adopted). Moreover, even if investors had subscribed to commercial data vendor services, there existed a significant mismatch between their databases. Kern and Morris (1994) compare two popular commercial databases at the time, Value Line and Compustat, and find material disagreements between the two datasets from 1985 to 1990. More importantly, they replicate Porcano (1986) using each database to show that empirical research could have different outcomes depending on the database used. Kothari, Shanken, and Sloan (1995) explore the implications of a selection bias in the Compustat data for return predictability. Therefore, the costs of obtaining *accurate* financial information were still very high, even after paying the stiff fees that the commercial data vendors had charged.

Lastly, in principle, investors could have received the financial documents directly from the companies by mail. Besides the costs of a long wait, this was not a viable option for an investor who intended to perform cross-sectional firm characteristics analysis because such analyses require simultaneous availability of financial information concerning many public companies.

B. Introduction of EDGAR

Responding to the call for more transparency and easier accessibility of corporate filings by publicly traded companies, the SEC took advantage of the advances in information technology by developing and introducing the EDGAR system. The SEC began developing the system in 1983. Eventually, after extensive testing, on February 23, 1993, the Commission issued four releases adopting the rules that required filers to file electronically. The process began on April 26, 1993, gradually bringing all filers onto the EDGAR system. EDGAR allows the public firms to disclose their financial information electronically, and investors or any other information consumers to access the filed corporate information instantaneously via the internet without charge.

The introduction of EDGAR significantly lowered the costs of information acquisition by expediting electronic filing and information dissemination via the internet. The SEC website points out that EDGAR "… benefits investors, corporations, and the U.S. economy overall by increasing the efficiency, transparency, and fairness of the securities markets... Access to EDGAR's public database is *free*—allowing you to research, for example, a public company's financial information and operations by reviewing the filings the company makes with the SEC." Furthermore, EDGAR's search function and other interface features allowed the users to retrieve specific information in electronic documents that may not be available in commercial databases.

A feature of EDGAR implementation, of paramount importance to our empirical design, is that the SEC adopted EDGAR following a phase-in schedule. The schedule assigned each public firm that required filing to one of ten phases (from Group CF-01 to Group CF-10). Each phase had a designated date as of which electronic filling was mandated (SEC Release No. 33-6977). The firms in the first group were mandated to start uploading filings through EDGAR on April 26, 1993, and those in the last group on May 1, 1996. Table I shows the implementation schedule.

We estimate the extent to which the investor information costs decreased. The staggered nature of the EDGAR implementation helps us better identify the effect of information costs, alleviate alternative explanations, and control for other confounding factors. For example, one alternative explanation could be that the equity market is becoming increasingly efficient and non-information costs decrease over time. However, to explain our results, these trends would have to discontinuously change for each firm at exactly the time at which it starts filling with EDGAR, a highly implausible set of circumstances. We also check that the ten implementation phases were similar pre-EDGAR in terms of anomaly alphas.

3. Data and Methodology

A. The SEC EDGAR Implementation Data

To construct anomaly portfolios for firms in each implementation phase, we first identify the date each firm becomes an EDGAR filer by examining the SEC Release No. 33-6977. We also incorporate all the subsequent changes and corrections to the initial phase-in list.[9] The SEC Release documents provide the list of company names and their Central Index Key (CIK). We manually match each firm to their record in Compustat using the company name and the CIK. We then use the linking file provided by the WRDS to link Compustat with CRSP. The last column of Table 1 reports the number of firms in each phase that we were able to match to the two databases.

B. The Anomalies

We start by examining a total of 320 anomalies replicated and shared by Chen and Zimmermann (2020), covering almost all the return signals that researchers have discovered to date.[10] By analyzing a comprehensive set of anomalies, we capture the full ramification of the information cost-saving effect of the EDGAR introduction on the anomalies' profitability. We follow Chen and Zimmermann (2020), who in turn follow the original academic papers that introduced each anomaly, their filters and datasets including CRSP, Compustat, IBES, the SEC's Form 13Fs, and

[9] The subsequent changes and corrections to the initial EDGAR phase-in list reported in SEC Release No. 33-6977 can be found in the SEC Release documents No. 33-7063, No. 34-34097, No. 33-7156, No. 34-35572, No. 33-7258, No. 34-36737, No. 33-7215, and No. 34-36220.

[10] Specifically, Chen and Zimmermann (2020) documents all the anomalies in Hou, Xue, and Zhang (2020), 98% of the anomalies in McLean and Pontiff (2016), 90% of anomalies in Green, Hand, and Zhang (2017), and 90% of the anomalies in Harvey, Liu, and Zhu (2016). We thank Andrew Chen and Tom Zimmerman for sharing the anomaly signal generating codes.

the Federal Reserve Economic Data (FRED). Chen and Zimmermann (2020) provide the quarterly versions of the anomalies by modifying the original characteristics to incorporate quarterly instead of annual information (assuming the standard one-quarter lag for quarterly data availability). Following this approach, we convert nine additional anomalies from annual to quarterly versions.[11]

We exclude penny stocks, that is, firms with a market capitalization below $50 million or a stock price lower than $5, because these stocks are not sufficiently liquid to be traded by institutional investors. Applying the two stock-level filters also mitigates the concern that the microcap returns shape our results (Hou, Xue, and Zhang (2020)). Also, our results primarily rely on value-weighted anomaly portfolio alphas, thus further mitigating the microcap concern. We adjust stock returns for delisting bias following the approach of Shumway (1997).[12]

We eliminate anomalies that rely on binary signals, are unprofitable pre-EDGAR, or are too correlated with each other (we keep one of the pair). We first drop anomalies with binary signals, such as whether a firm had paid dividends last month, because we cannot form decile portfolios for such anomalies. Next, we compute the Fama and French three-factor alphas (Fama and French (1992, 1993)) and the pairwise return correlation of the decile equal-weighted anomaly portfolio returns over a ten-year period pre-EDGAR, from October 1983 to September 1993.[13] Then, in the spirit of Green, Hand, and Zhang (2017), we exclude the anomalies that have negative pre-EDGAR alphas. Arbitrageurs would have been unlikely to trade anomalies without positive

[11] The nine anomalies are: accruals, sales growth over inventory growth, sales growth over overhead growth, change in sales vs change in receivables, revenue growth rank, change in depreciation to gross PPE, change in gross margin versus sales, change in sales to inventory, net income/book equity.

[12] If neither the last return nor the delisting return is available and the deletion code is in the 500s—which includes 500 (reason unavailable), 520 (became traded over the counter), 551–573 and 580 (various reasons), 574 (bankruptcy), and 584 (does not meet exchange financial guidelines)—the delisting return is assigned to be –30%. If the delisting code is not in the 500s, the last return is set to –1.0.

[13] We use the Fama and French *three*-factor alphas to filter out unprofitable anomalies because the Fama and French *three*-factor model was known to the investors at the time of EDGAR implementation whereas the Fama and French *five*-factor model was still not known to the public. Therefore, using the Fama and French *three*-factor alphas allows us to better capture the actual investors' trading activity prior to the introduction of EDGAR.

alphas, and it is not clear how to capture alpha attenuation due to EDGAR for such anomalies. Finally, to ensure that we focus on relatively independent anomalies, we identify "twin" anomalies that have a pairwise return correlation above 0.9 and eliminate ZZ anomalies by dropping one of the twins. Our final sample includes 205 anomalies.

Next, we compute the benchmark-adjusted anomaly monthly returns over January 1992 to December 1997 sample period for the final sample of 205 anomalies, after controlling for the Fama-French five-factor alphas adjusted for momentum (henceforth the Fama-French six-factor alpha) for the equal-weighted and value-weighted decile and quintile portfolio returns. Jensen, Kelly, and Pedersen (2021) emphasize the importance of focusing on anomaly alphas instead of anomaly returns. We focus on alphas, but our results hold if we do not risk-adjust anomaly returns.

4. Results

A. Baseline Difference-in-Difference Results

EDGAR provides free and instant online access to SEC filings and thus lowers information costs. EDGAR makes it easier for arbitrageurs to identify which EDGAR filer stocks are mispriced. Accordingly, the profitability of anomaly portfolios constructed from EDGAR filer stocks should weaken. Only the anomalies that rely on accounting information from EDGAR should attenuate.

We first compute the alpha for top-minus-bottom portfolio for a given anomaly, implementation phase, and month in two steps. First, we compute the difference between the top and bottom decile (quintile) portfolio returns, aggregated in the equal-weighted (value-weighted) manner, for each anomaly, phase, and month. Second, the alpha is calculated in a standard way as the sum of the residuals and the average alpha (intercept) from a regression of top-minus-bottom portfolio return on Fama-French factors, estimated over the sample period.

Our baseline specification estimates the effect of EDGAR implementation on the anomaly portfolio profitability using a standard difference-in-difference framework:

$$\widehat{\alpha_{a,p,t}} = \gamma_t + \gamma_a + \beta_1 * Post_{p,t} + \beta_2 * Post_{p,t} * ACC_a + \epsilon_{a,p,t}. \quad (1)$$

The dependent variable, $\widehat{\alpha_{a,p,t}}$, is the Fama-French six-factor alpha, of the anomaly a top-minus-bottom portfolio in month t for phase p; γ_t are monthly time fixed effects; γ_a are anomaly fixed effects; $Post_{p,t}$ is an indicator variable equal to one if month t is on or after the effective date for phase p, and equal to zero before that date; and ACC_a is an indicator variable that equals one if a is an accounting anomaly, and equals zero if a is a non-accounting anomaly. The standard errors are clustered by anomaly and month to address the potential correlation in errors (Petersen, 2009).

Table II presents the results. The dependent variables in the four columns are the Fama-French six-factor alphas for decile (1-10) or quintile (1-5), equal-weighted (EW) or value-weighted (VW) portfolios. The portfolio alphas and the coefficients are expressed in percentages. As shown at the bottom of Table II, accounting-based anomaly alphas decline by 47 to 62 basis points per month (or 5.7% to 7.4% per year) because of the EDGAR introduction. This decline completely offsets the average accounting anomaly alphas of 52.9 basis points per month from the pre-EDGAR period. In contrast, as shown in the top row of Table II, non-accounting alphas do not decline post-EDGAR. The difference between the two, captured by the difference-in-difference coefficient, β_2, is between 42 and 49 basis points per month across different specifications, statistically significant at the one-percent level.

This pivotal gap captures the costs of information acquisition that investors incurred without EDGAR. EDGAR is free and convenient to use, slashing the costs of acquiring information. Therefore, that amount of information cost-saving effect (the total profit from the arbitrageurs' point of view) is quickly arbitraged away, resulting in a profitability attenuation of

42-49 basis points per month thereafter. Accordingly, the 42-49 basis points per month gap measures the amount of information acquisition costs investors faced in the absence of EDGAR.

These findings show that the information costs can be as important as other limits-to-arbitrage related costs that arbitrageurs face in a market with frictions. There is a debate about the extent to which short sale costs affect anomaly profitability. Geczy, Musto, and Reed (2002) show that stock borrow fees explain a small portion of anomaly returns. In contrast, Chu, Hirshleifer, and Ma (2020) show that relaxed short sale constraints reduce abnormal returns of 11 anomalies by 72 basis points per month. The pilot program of Regulation SHO that they study lifted the uptick rule, which only allowed a short sale at a higher price than the previous trade. A similar debate is ongoing on the effect of trading costs on anomaly profitability. Using TAQ data, Novy-Marx and Velikov (2015) show that the average trading costs range from 20 to 57 basis points per month for the mid-turnover anomalies. In contrast, Frazzini, Israel, and Moskowitz (2018) argue that institutional trading costs are much smaller than the effective bid-ask spreads in TAQ. Also, arbitrageurs can lower costs by optimizing how they turnover anomaly portfolios (Novy-Marx and Velikov (2019), DeMiguel et al. (2020)). Although our results do not speak to the two debates, the 47 to 62 basis points per month decline in anomaly profitability attributable to information costs is comparable to the upper bounds for the trading and short sale costs. Also, investors need to acquire information to identify which stocks to buy or sell before they start trading. Therefore, investors incur information costs even before they pay trading or short sale costs.

Figure 1 illustrates how the average anomaly alphas of the treatment and control groups responded to the EDGAR implementation. It reiterates the salient features of our regression results from Table II. The treatment group—accounting anomalies—experiences a sharp decline in average alphas, from 0.73, 0.78, two and one months before EDGAR implementation, to 0.58

percent at the EDGAR implementation date, to the substantially lower values of EDGAR implementation for the affected stocks to -0.13, 0.23, and 0.22 percent per month during the first three months following EDGAR implementation. At the same time, the average alphas of non-accounting anomalies—the control group—did not experience such a large decline. If anything, they increased by about 15 basis points per month, as documented by the full blue lines covering pre- and post-EDGAR implementation periods in Figure 1.

B. EDGAR Effects and Information Availability

The EDGAR-prompted decline in profitability of accounting anomalies stems from a change in accounting information availability. That change should be more pronounced among the stocks for which the information was more difficult to gather in the pre-EDGAR period. To test this hypothesis, we use two empirical proxies for information availability—analyst coverage and market capitalization (e.g., Kelly and Ljungqvist (2012))—to classify stocks into high or low information-availability groups. For example, full-service broker-dealers provided their clients with analysts' research and opinions in addition to executing trades as part of an overall package of services (the so-called "soft" dollar arrangements).

We also want to confirm the main results from the previous section (based on decile/quintile portfolio sorts) using an alternative two-stage approach inspired by Fama-MacBeth regression methodology. In the first stage, we estimate a linear cross-sectional regression of how a given anomaly predicts returns for a given phase and month. The second stage remains the standard difference-in-difference regression in Equation (1), except the dependent variable is the linear slope estimated from the first stage instead of the top-minus-bottom portfolio alpha. We will conduct this analysis separately for stocks with high and low information availability.

To gauge information availability, we first compute the average analyst coverage and market capitalization pre-EDGAR, from January 1990 to December 1992, and then classify each stock i as high-information, h (above-median analyst coverage; above-median market capitalization of equity), or low-information, l (below-median analyst coverage; below-median market capitalization of equity). For each of the 125 accounting anomalies, for each implementation phase, and for every month from 1992 to 1997, we estimate two first-pass regressions of the form

$$R_{i,a,p,t+1} = \alpha + \beta_{a,p,t} * SignalPercentile_{i,a,p,t} + \epsilon_{i,a,p,t}, \tag{2}$$

separately for high and low information availability stock groups. For each group, firm i is assigned to phase p for accounting anomaly a in month t; $R_{i,a,p,t+1}$ is the next-month return for stock i; $SignalPercentile_{i,a,p,t}$ is anomaly signal's percentile within stocks in phase p for anomaly a in month t. $\beta_{a,p,t}$ is the coefficient of interest. This first-pass regression step creates a panel of $\widehat{\beta_{h/l,a,p,t}}$, monthly beta estimates for information availability groups h/l (high or low). Next, we estimate the second-pass panel regression, similar to Equation (1):

$$\widehat{\beta_{h/l,a,p,t}} = \gamma_t + \gamma_a + \delta_1 * Post_{p,t} + \delta_2 * LoInfo_{h/l,a,p,t} + \delta_3 * Post_{p,t} * LoInfo_{h/l,a,p,t} + \epsilon_{h/l,a,p,t}, \tag{3}$$

where $\widehat{\beta_{h/l,a,p,t}}$ are the monthly beta estimates from the first-pass regressions; γ_t and γ_a are monthly and anomaly fixed effects; $Post_{p,t}$ is an indicator variable that equals one if month t is after the effective date for phase p and equals zero otherwise; and $LoInfo_{a,p,t}$ is an indicator variable that equals one for all $\widehat{\beta_{h/l,a,p,t}}$ associated with low information availability groups and equals zero for all $\widehat{\beta_{h/l,a,p,t}}$ associated with high information availability groups.

The results are presented in Table III. Panels A and B focus on analyst coverage and market capitalization, respectively. Across both panels, the accounting anomaly profitability decline associated with the EDGAR introduction is primarily driven by stocks with low information availability (stocks followed by fewer analysts or stocks with below-median market capitalization)—approximately 70-71 basis points per month, or about 8.5% per year, with the corresponding *t*-statistic of -3.2. In contrast, the EDGAR-prompted profitability decline for accounting anomalies in the domain of high information availability stocks is statistically indistinguishable from zero. These findings confirm that intuition that the effects of EDGAR introduction are particularly pronounced in the domain of stocks for which information was particularly costly to acquire pre-EDGAR.

C. Baseline Analyses Revisited: Long and Short Anomaly Portfolio Legs

In this and following subsections, we study how the attenuation of accounting anomaly portfolio profitability propagates through the equity market and affects different outcomes. We first focus on a well-known asymmetry between the short and long legs of equity anomalies. For example, Stambaugh, Yu, and Yuan (2012) find that 11 anomalies they study are concentrated primarily in the short legs.

The results, presented in Table IV, confirm that profit attenuation effects are concentrated among the short legs of the accounting anomaly portfolios. Across all four columns of Table IV, the difference-in-difference coefficient estimates for the long leg accounting anomaly portfolios are small and statistically indistinguishable from zero. By contrast, the difference-in-difference coefficient estimates, statistically significant at the 1-percent level across all columns of the table, are 32 to 50 basis points per month. These estimates are comparable to the difference-in-difference coefficient estimates of 42 to 49 basis points from the baseline specification from Table II. These results suggest that short sale constraints can interact and elevate information costs.

D. Understanding the Mechanism behind the Attenuation of Anomaly Profitability

Lower costs of acquiring accounting information should make stock prices more efficient, reduce information asymmetry, and improve liquidity. We confirm this hypothesis using idiosyncratic volatility as a proxy for price (in)efficiency and Amihud (2002) measure for illiquidity.[14] We also examine trading turnover, a broad measure of the effect of EDGAR on investors' trading activity.

We first estimate how stocks in the top and bottom anomaly portfolios differ from stocks in other portfolios on the three measures of interest. We estimate a cross-sectional regression for for every anomaly a, phase p, and month t:

$$Measure_{i,a,p,t} = \beta_0 + \beta_{a,p,t} * Treated_{i,a,p} + \epsilon_{i,a,p,t}\,, \tag{4}$$

where $Measure_{i,a,p,t}$ is idiosyncratic volatility, Amihud illiquidity, or stock turnover, and $Treated_{i,a,p}$ equals one if stock i is in a top or bottom decile portfolio, and zero otherwise. Next, we estimate for each of the three measures the second-pass cross-sectional regression similar to that from Equation (1):

$$\widehat{\beta_{a,p,t}} = \gamma_t + \gamma_a + \delta_1 * Post_{p,t} + \delta_2 * Post_{p,t} * ACC_a + \epsilon_{a,p,t}. \tag{5}$$

The dependent variable, $\widehat{\beta_{a,p,t}}$, is the sensitivity estimate from the first-stage cross-sectional regression (Equation (4)); γ_t and γ_a are monthly and anomaly fixed effects; $Post_{p,t}$ is an indicator variable equal to one if month t is on or after the effective date for phase p; and ACC_a is an indicator variable that equals one if a is an accounting anomaly, and equals zero if a is a non-accounting anomaly. The standard errors are clustered by anomaly and month.

[14] Idiosyncratic volatility is the standard deviation of the regression residual from the Fama-French six-factor model, estimated from daily return data from the past month. Amihud illiquidity measure is defined as the past twelve-month average of daily return divided by dollar volume.

Table V reports the results. In line with the expectations, the EDGAR filer stocks in the decile accounting anomaly portfolios (treatment group) exhibit lower idiosyncratic volatility, higher trading volume, and lower Amihud illiquidity index in response to EDGAR introduction. At the same time, the EDGAR filer stocks in the *non*-accounting anomaly decile portfolios also exhibit statistically significant economic effects. Idiosyncratic volatility drops, albeit less sharply than it does for accounting anomalies. Amihud illiquidity also drops and does so to an even higher extent than is the case for accounting anomalies.[15] Finally, non-accounting anomaly trading volume increases more than accounting anomaly trading volume does.

E. Short Interest and Institutional Ownership

In this section, we study how investors' trading activity measures respond to the EDGAR implementation. Table IV shows that accounting anomaly profit attenuation is driven by portfolio short legs. An immediate implication of this finding is that the accompanying activity by short-sellers, reflected in stock short interest, ought to be more informative than the accompanying activity by long-only investors, reflected in stock institutional ownership. To test this hypothesis, we conduct two separate analyses, one for the long side and the other for the short side of the anomaly portfolios. For the long leg, we first estimate the following cross-sectional regression:

$$Measure_{i,a,p,t} = \beta_0 + \beta_{a,p,t} * TreatedLong_{i,a,p} + \epsilon_{i,a,p,t} \ . \tag{6}$$

Analogously, for the short leg, we first estimate:

$$Measure_{i,a,p,t} = \beta_0 + \beta_{a,p,t} * TreatedShort_{i,a,p} + \epsilon_{i,a,p,t} \ . \tag{7}$$

[15] While we do not explore liquidity measures based on intraday data such as the bid-ask spread and price impact, Goyenko et al. (2009) show that Amihud illiquidity is strongly correlated with these measures.

In these regressions, $Measure_{i,a,p,t}$ is short interest or institutional ownership, and $TreatedLong_{i,a,p,t}$ ($TreatedShort_{i,a,p,t}$) is an indicator variable that equals one if stock i is an EDGAR filer in the long (short) leg of the decile portfolio for anomaly a, in phase p, at time t, and zero otherwise. Next, we estimate for each of the two measures the second-pass cross-sectional regression, separately for the long and short legs, as in Equation (4).

The results are reported in Table VI. Its Panel A presents the results for both long and short legs of anomaly portfolios, revealing no changes in institutional ownership for the long leg, as well as a sizeable, eight-percent increase in institutional holdings for both accounting and non-accounting anomalies, with their difference near zero and statistically insignificant. At the same time, the short leg short interest level has dropped considerably more for accounting anomalies than for non-accounting anomalies (-12.59 percent versus -8.93 percent, a -3.65 percent difference, statistically significant at the one-percent level).

Overall, that short interest increased for the long anomaly leg and decreased for the short leg, while institutional ownership changed similarly for the treatment and control groups is quite intuitive. First, because anomaly attenuation is concentrated in the short leg, we expect that short sellers respond more than long only investors do, suggesting that short interest should respond more than institutional ownership does. Second, pre-EDGAR, many stocks in the short leg of anomalies had had negative expected alphas, which short sellers had exploited. The EDGAR introduction made prices more efficient and fewer stocks in the short leg have had negative expected alphas in its aftermath, which, in turn, prompted short sellers to reduce their short positions. Put differently, short interest declined in response the EDGAR introduction because of fewer opportunities on the short side.

Short interest increased for the long leg of anomalies for the same reason. Pre-EDGAR, most stocks in the long leg had had positive expected alphas and only a few of them had had negative expected alpha, resulting in few opportunities for short sellers and, accordingly, low short interest. The EDGAR introduction made the average expected alpha for the long leg of accounting anomalies close to zero, which can be viewed as about an even split between positive and negative alphas for individual stocks in the long leg. Therefore, the EDGAR introduction provided more opportunities for short sellers of long-leg stocks and short interest has increased relative to pre-EDGAR.

5. Robustness Tests

A. Concerns Regarding the First Implementation Phase

In our setting, a pivotal ingredient of successful identification is the random nature of assignment of firms to implementation phases. If phase assignment is partly driven by considerations other than random assignment, there is room for a concern that shocks to the EDGAR filers' information environment are not entirely exogeneous. Indeed, before the EDGAR rollout in April 1993, the SEC called for volunteers to file electronically. This trial confirmed the integrity of the EDGAR system before engaging in a full-fledged implementation. The volunteer firms were subsequently assigned to the first implementation phase. Thus, because of self-selection, the assignment for the first phase was not entirely random.

Also, accounting information for the first phase was available with a delay. The public can freely access EDGAR only after January 17, 1994 (Goldstein, Yang, and Zuo (2020), Chang, Ljungqvist, and Tseng (2021)); before January 1994, investors had access to EDGAR through Mead Data Central. Given the standard three-month information lag assumption we introduce, if

EDGAR were not easily available prior to January 1994, the first phase would have little cost-saving effect because its effective date (October 1, 1993) falls before January 1994. The remaining implementation phases (from CF-02 to CF-09) are unaffected by these issues because their effective dates are after January 1994.

We address these concerns by repeating the baseline difference-in-difference analysis after dropping the first implementation phase. The results, presented in Table VII, are very similar to those reported in Table II, thus alleviating concerns associated with the first EDGAR implementation phase. Indeed, as shown toward the bottom of Table VII, accounting-based anomaly alphas decline by 46 to 62 basis points per month (or 5.5% to 7.4% per year) because of the EDGAR introduction. In contrast, as shown in the top row of Table VII, non-accounting alphas do not decline post-EDGAR. The difference between the two, captured by the difference-in-difference coefficient, β_2, is between 42 and 53 basis points per month across different specifications, statistically significant at the one-percent level.

Another potential concern is that a small subset of implementation phases could be driving the results. Table A.I in the Appendix documents the contribution of each implementation phase. While the effect of EDGAR introduction on anomaly returns varies across phases, there is no clear pattern, and excluding any one phase has negligible effect on the overall results.

B. Pre-trends and Falsification Tests

One of the key assumptions of the difference-in-difference analysis is the parallel trend assumption. We formally test this assumption following the methodology from Gao and Huang (2020). Specifically, we estimate the baseline difference-in-difference regression over a four-year period *prior to* the actual EDGAR implementation, using pseudo-event dates. The pseudo-events of each EDGAR implementation phase are assumed to take place two years *before* the actual phase dates.

Accordingly, the indicator variable $Post_{p,t}$ is redefined to equal one if month t is after the first *pseudo*-event date on which investors presumably trade on the latest EDGAR information related to the new EDGAR filers, and is equal to zero if month *t* is before that pseudo-event date. Panel A of Table VIII presents the result for the pre-trend test. The results show that the parallel trend assumption is likely to hold in our difference-in-difference setting.

We also run a falsification test. Again, applying the methodology in Gao and Huang (2020), we estimate the baseline difference-in-difference regression over a four-year period *following* the actual EDGAR implementation, using the pseudo-event dates from two years *after* the actual phase dates. The indicator variable $Post_{p,t}$ is redefined accordingly. Panel B of Table VIII reports the results for the falsification test.

C. Dropping annual siblings, thin portfolios

In this section, we address two potential issues: annual and quarterly versions of the same anomaly conceivably could be highly correlated and some anomaly portfolios could contain only a few stocks. First, as discussed in Section III.B, we constructed the sample of 205 anomalies by following the process introduced in Chen and Zimmermann (2020). That process resulted in 23 anomalies in the sample based on both annual and quarterly portfolio formation, introducing the issue of potential double-counting. At the outset, returns for these "sibling" anomalies pass the correlation filter described in Section III.B and, thus, contain independent information. Nonetheless, to provide additional comfort with our results, we further address the issue of potential double-counting by estimating our baseline results from Table II on the sample of 182 anomalies, obtained from the full sample of 205 anomalies by dropping the "sibling" anomalies that feature portfolio construction based on annual updates. The results, presented in Panel A of

Table IX, are virtually identical to those from Table II, indicating that the presence of annual siblings in the full sample of 205 anomalies does not drive our results.

Second, the portfolio construction of long and short legs of an anomaly in each implementation phase (particularly the later ones) could result in "thin" portfolios, consisting of relatively few stocks. This, in turn, could make our estimates more variable and thus imprecise. However, this issue would affect only few portfolios. Nonetheless, to alleviate this concern, we replicate our baseline results from Table II with the added step of dropping all the observations based on "thin" portfolios consisting of fewer than five stocks in either long or short leg of the portfolio. This step creates a gently unbalanced panel by marking some anomaly-phase-months with few stocks as missing. Once again, the results, presented in Panel B of Table IX, are virtually identical to those from Table II. Therefore, the issue of "thin" portfolios does not affect our results.

6. Conclusion

In this paper, we investigate the causal effect of the information acquisition costs on the anomaly portfolio returns. We use the SEC's EDGAR implementation as a quasi-exogenous shock that lowers the costs of acquiring accounting information. Using the difference-in-difference framework, we find that alphas of accounting anomalies attenuate on average by 47 to 62 basis points per month (or 5.7% to 7.4% per year) in response to the EDGAR introduction. This decline explains away all of the pre-EDGAR accounting anomaly alphas. In contrast, the profitability of the non-accounting anomalies remains largely unaffected by the EDGAR introduction.

The profitability attenuation translates to the costs of acquiring accounting information (Grossman and Stiglitz (1980)) that investors had to bear in the absence of the EDGAR system. To the best of our knowledge, this paper is the first to estimate information costs and show that they are comparable to trading or short sale costs. While non-information costs are extensively studied (Keim and Madhavan (1997), Korajczyk and Sadka (2004), Lesmond, Schill, and Zhou (2004), Novy-Marx and Velikov (2015), Frazzini, Israel, and Moskowitz (2018), and Patton and Weller (2020) study trading costs; Geczy, Musto, and Reed (2002), Drechsler and Drechsler (2014), and Chu, Hirshleifer, and Ma (2020) study short sale costs), the study of information costs is in its nascent stage.

We further explore how the effect of EDGAR on anomalies propagates to other market variables. First, we find that this effect is concentrated in stocks for which accounting information was particularly hard to acquire pre-EDGAR. Second, the alpha attenuation is concentrated in the short leg of anomaly portfolios. Next, we confirm that stocks in the top/bottom portfolios became more efficiently priced and more liquid because of EDGAR. Finally, as these stocks are less mispriced, they attract fewer short sellers and other arbitrageurs.

Our results remain highly relevant for today's markets. To generate alpha, investors strive to establish information advantage by acquiring novel data and analyzing it in unique ways. Pre-EDGAR, accounting data was at the cutting edge of investors' data exploration efforts. The EDGAR implementation made accounting data widely available and thus less useful for generating alpha. Arbitrageurs move on to other, more costly, and thus less explored data. Our conclusions likely extrapolate to the alternative data.

Data and information that it produces are central to arbitrageurs' success. For example, Citadel CEO Ken Griffin notes that, "[o]ur ability to leverage big data effectively in our investment process is critical to our success as a firm" (Randle (2018)). Many hedge funds introduced Chief Data Officer positions to highlight the importance of the data. Our paper offers an initial systematic attempt to understand the role that information costs play in the investment process.

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Table I: The SEC EDGAR Implementation Schedule

This table shows the SEC's implementation timeline of EDGAR as recorded in the SEC Release documents. The announced implementation date is the date which the SEC mandated the assigned firms of a given implementation phase to start filing their financial statements electronically via EDGAR. The effective date is defined as the first date as of which investors start trading the EDGAR filers stocks (for a given implementation phase) using the latest financial information on the EDGAR filers retrieved from EDGAR. Following the standard one-quarter lag assumption of the quarterly accounting data availability in the anomaly literature, investors must wait for one quarter until the effective date for the recent information to become available on EDGAR before they can start trading on the EDGAR filer stocks using the newly acquired information. The number of EDGAR filer stocks is the number of stocks that are successfully matched to the Compustat and CRSP database.

Implementation Phase	Implementation Date	Year-Quarter of the Phase	Effective Date	# of EDGAR Filer Stocks Captured by Phase
1	4/26/1993	1993Q2	10/1/1993	149
2	7/19/1993	1993Q3	1/1/1994	541
3	10/4/1993	1993Q4	4/1/1994	564
4	12/6/1993	1993Q4	4/1/1994	737
5	8/1/1994	1994Q3	1/1/1995	1,033
6	11/1/1994	1994Q4	4/1/1995	866
7	5/1/1995	1995Q2	10/1/1995	858
8	8/1/1995	1995Q3	1/1/1996	756
9	11/1/1995	1995Q4	4/1/1996	386
10	5/1/1996	1996Q2	10/1/1996	2,723

Table II

The Baseline Difference-in-Difference Estimates

This table presents the coefficients from the baseline difference-in-difference anomaly portfolios regression from Equation (1). $Post_{p,t}$ is an indicator equal to one if month t is on or after the implementation date for phase p, and equal to zero if month t is before that date; ACC_a is an indicator variable that equals one if a is an accounting anomaly, and equals zero if a is a non-accounting anomaly. The dependent variables $\widehat{\alpha_{a,p,t}}$ in the four columns of the table are the Fama-French six-factor alphas for quintile (1-5) or decile (1-10), equal-weighted (EW) or value-weighted (VW) portfolios. All specifications contain anomaly and monthly fixed effects. The sample extends over 205 anomalies in the period from January 1992 to December 1997. The portfolio alphas and the coefficients are expressed in percentages. The standard errors are clustered by anomaly and by month to address the potential correlation in errors. Robust t-statistics are presented in parentheses below the estimates. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	FF6 Alpha 1-5 EW	FF6 Alpha 1-5 VW	FF6 Alpha 1-10 EW	FF6 Alpha 1-10 VW
$Post_{p,t}$	-0.066	-0.042	-0.120	-0.123
(non-accounting anomalies)	(-0.63)	(-0.34)	(-0.95)	(-0.88)
$Post_{p,t} * ACC_a$	-0.419***	-0.429***	-0.421***	-0.494***
(difference-in-difference)	(-3.55)	(-3.69)	(-3.11)	(-3.47)
Post-estimation test:				
$Post_{p,t} + Post_{p,t} * ACC_a$	-0.485***	-0.471***	-0.541***	-0.617***
(accounting anomalies)				
Mean of Dependent Variable	0.301	0.231	0.332	0.281

Table III

Information Availability and Accounting-based Anomaly Portfolio Profitability

This table shows the regression results for high and low information availability groups of accounting-based anomaly portfolios. To classify stocks into high or low information availability groups, we first compute the average analyst coverage and market capitalization of equity for all EDGAR filers from January 1990 to December 1992, and then classify each stock i as high-information, h, (above-median analyst coverage, Panel A; above-median market capitalization of equity, Panel B) or low-information, l (below-median analyst coverage, Panel A; below-median market capitalization of equity, Panel B). For each of the 125 accounting anomalies, for every phase p, and for every month from January 1992 to December 1997 we estimate two first-pass regressions (Equation (2)) separately for high-information and low-information availability groups of stocks. The two first pass regressions together create a panel of $\widehat{\beta_{h/l,a,p,t}}$, monthly beta estimates for each information group h/l (high or low), accounting-based anomaly a portfolio constructed with the group h or l stocks, in a given phase p. Next, we estimate the second-pass regression from Equation (3). All specifications contain anomaly and monthly fixed effects. The standard errors are clustered by anomaly and by month to address the potential correlation in errors. Robust t-statistics are presented in parentheses below the estimates. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Panel A: Analyst coverage among EDGAR filers		
	(1) Low analyst coverage $\delta_1+\delta_2+\delta_3$	(2) High analyst coverage δ_1	(1) – (2) Difference $\delta_2+\delta_3$
$Post_{p,t}$	-0.706***	0.032	-0.739***
	(-3.27)	(0.17)	(2.74)
	Panel B: Market capitalization among EDGAR filers		
	(1) Small size EDGAR filers $\delta_1+\delta_2+\delta_3$	(2) Large size EDGAR filers δ_1	(1) – (2) Difference $\delta_2+\delta_3$
$Post_{p,t}$	-0.701***	-0.100	-0.608*
	(-3.23)	(-0.46)	(1.91)

Table IV
Dynamics of Long and Short Leg Anomaly Portfolios

This table presents the coefficients from the baseline difference-in-difference regression (Equation (1)), estimated separately for the long (Panel A) and short (Panel B) legs of the 205 anomaly portfolios. $Post_{p,t}$ is an indicator equal to one if month t is on or after the implementation date for phase p, and equal to zero if month t is before that date; ACC_a is an indicator variable that equals one if a is an accounting anomaly, and equals zero if a is a non-accounting anomaly. The dependent variables $\widehat{\alpha_{a,p,t}}$ in the four columns of the table are the Fama -French six-factor long (Panel A) or short (Panel B) alphas for quintile (1-5) or decile (1-10), equal-weighted (EW) or value-weighted (VW) portfolios. All specifications contain anomaly and monthly fixed effects. The sample extends over 205 anomalies in the period from January 1992 to December 1997. The portfolio alphas and the coefficients are expressed in percentages.

	FF6 Alpha 1-5 EW	FF6 Alpha 1-5 VW	FF6 Alpha 1-10 EW	FF6 Alpha 1-10 VW
	Panel A: Long Leg Accounting Anomaly Portfolios			
$Post_{p,t}$	-0.221	0.0310	-0.238	-0.0316
(non-accounting anomalies)	(-1.29)	(0.25)	(-1.28)	(-0.21)
$Post_{p,t} * ACC_a$	-0.000373	-0.126	0.0591	-0.0445
(difference-in-difference)	(-0.00)	(-1.26)	(0.51)	(-0.35)
Post-estimation test:				
$Post_{p,t} + Post_{p,t} * ACC_a$	-0.221	-0.095	-0.179	-0.076
(accounting anomalies)	(-X.XX)	(-X.XX)	(-X.XX)	(-X.XX)
Mean of Dependent Variable	0.674	0.566	0.668	0.569
	Panel B: Short Leg Accounting Anomaly Portfolios			
$Post_{p,t}$	0.128	-0.0879	0.0989	-0.100
(non-accounting anomalies)	(0.70)	(-0.56)	(0.48)	(-0.55)
$Post_{p,t} * ACC_a$	-0.431***	-0.324***	-0.499***	-0.482***
(difference-in-difference)	(-4.07)	(-3.16)	(-3.77)	(-3.44)
Post-estimation test:				
$Post_{p,t} + Post_{p,t} * ACC_a$	-0.303**	-0.412***	-0.400***	-0.582***
(accounting anomalies)				
Mean of Dependent Variable	-0.291	-0.288	-0.250	-0.230

Table V
Investor Ressponse to EDGAR Implementation

This table shows the response of three stock-related measures to EDGAR implementation. We first estimate a cross-sectional regression for each measure, for every stock, for all 205 anomalies, for every EDGAR implementation phase, and for every month from January 1992 to December 1997 using Equation (4). We then estimate the second-pass panel regression from Equation (5). The sample period is from January 1992 to December 1997. All specifications contain anomaly and month fixed effects. The standard errors are clustered by anomaly and by month to address the potential correlation in errors. Robust *t*-statistics are presented in parentheses below the estimates. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	(1) Accounting Anomalies $\delta_1 + \delta_2$	(2) Non-Accounting Anomalies δ_1	(1) – (2) Difference δ_2
	Panel A: Idiosyncratic Volatility		
$Post_{p,t}$	-0.0075***	-0.0070***	-0.0005***
	(-20.36)	(-20.24)	(-2.97)
Number of Anomalies	125	80	205
	Panel B: Amihud Illiquidity		
$Post_{p,t}$	-0.2171***	-0.2754***	0.0583***
	(-10.05)	(-11.38)	(4.23)
Number of Anomalies	125	80	205
	Panel C: Log of Trading Volume		
$Post_{p,t}$	0.5982***	0.6931***	-0.0949***
	(8.89)	(10.21)	(-5.02)
Number of Anomalies	125	80	205

Table VI

Changes in Institutional Ownership and Short Interest

This table shows how institutional ownership (Panel A) and short interest (Panel B) in the long and the short leg of the anomaly portfolios in the treatment group respond to EDGAR implementation. For the long (short) leg, we first estimate the respective cross-sectional regressions from Equations (6) and (7). We then estimate long (short) side panel regressions from Equation (5). The sample period is from January 1992 to December 1997. All specifications contain anomaly and month fixed effects. The standard errors are clustered by anomaly and by month to address the potential correlation in errors. Robust *t*-statistics are presented in parentheses below the estimates. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Treatment portfolio (1-10)	(1) Accounting Anomalies $\delta_1 + \delta_2$	(2) Non-Accounting Anomalies δ_1	(1) – (2) Difference δ_2
	Panel A: Institutional Ownership		
Long leg			
$Post_{p,t}$	0.0035	0.0025	0.0010
	(0.82)	(0.59)	(0.19)
Short leg			
$Post_{p,t}$	0.0797***	0.0794***	0.0003
	(8.54)	(9.24)	(0.09)
Number of Anomalies	125	80	205
	Panel B: Short Interest		
Long leg			
$Post_{p,t}$	0.0577***	0.0323***	0.0254***
	(5.06)	(2.77)	(2.91)
Short leg			
$Post_{p,t}$	-0.1259***	-0.0893***	-0.0365***
	(-6.02)	(-4.92)	(-4.56)
Number of Anomalies	125	80	205

Table VII
Excluding the First Implementation Phase

This table presents the coefficients from the baseline difference-in-difference anomaly portfolios regression from Equation (1). $Post_{p,t}$ is an indicator equal to one if month t is on or after the implementation date for phase p, and equal to zero if month t is before that date; ACC_a is an indicator variable that equals one if a is an accounting anomaly, and equals zero if a is a non-accounting anomaly. The dependent variables $\widehat{\alpha_{a,p,t}}$ in the four columns of the table are the Fama-French six-factor alphas for quintile (1-5) or decile (1-10), equal-weighted (EW) or value-weighted (VW) portfolios. All specifications contain anomaly and monthly fixed effects. The sample extends over 205 anomalies in the period from January 1992 to December 1997, with the observations associated with the first implementation phase excluded from the sample. The portfolio alphas and the coefficients are expressed in percentages. The standard errors are clustered by anomaly and by month to address the potential correlation in errors. Robust *t*-statistics are presented in parentheses below the estimates. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	FF6 Alpha 1-5 EW	FF6 Alpha 1-5 VW	FF6 Alpha 1-10 EW	FF6 Alpha 1-10 VW
$Post_{p,t}$	-0.0350	-0.0265	-0.0954	-0.0951
(non-accounting anomalies)	(-0.33)	(-0.21)	(-0.74)	(-0.67)
$Post_{p,t} * ACC_a$	-0.426***	-0.462***	-0.413***	-0.534***
(difference-in-difference)	(-3.45)	(-3.78)	(-2.86)	(-3.57)
Post-estimation test:				
$Post_{p,t} + Post_{p,t} * ACC_a$	-0.461***	-0.489***	-0.508***	-0.625***
(accounting anomalies)				
Mean of Dependent Variable	0.327	0.253	0.358	0.304

Table VIII
Pre-trends test, falsification test

This table presents the coefficients from the pre-trends and falsification tests of the baseline difference-in-difference regression results reported in Table II. Following Gao and Huang (2020), the regression reported in Panel A (Panel B) is estimated over a four-year period *prior to* (*following*) the actual EDGAR implementation, and the pseudo-event dates are assumed to take place 2 years *before* (*after*) the actual dates. $Post_{p,t}$ is an indicator equal to one if month t is on or after the implementation date for phase p, and equal to zero if month t is before that date; ACC_a is an indicator variable that equals one if a is an accounting anomaly, and equals zero if a is a non-accounting anomaly. The dependent variables $\widehat{\alpha_{a,p,t}}$ in the four columns of the table are the Fama-French six-factor alphas for quintile (1-5) or decile (1-10), equal-weighted (EW) or value-weighted (VW) portfolios. The sample extends over 205 anomalies in the period from January 1992 to December 1997. The portfolio alphas and the coefficients are expressed in percentages. All specifications contain anomaly and month fixed effects. The standard errors are clustered by anomaly and by month to address the potential correlation in errors. Robust t-statistics are presented in parentheses below the estimates. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	FF6 Alpha 1-5 EW	FF6 Alpha 1-5 VW	FF6 Alpha 1-10 EW	FF6 Alpha 1-10 VW
	Panel A: Pre-Trends Test			
$Post_{p,t}$	-0.436***	-0.345**	-0.485**	-0.412*
(non-accounting anomalies)	(-2.73)	(-2.04)	(-2.50)	(-1.80)
$Post_{p,t} * ACC_a$	0.250	0.112	0.326	0.197
(difference in difference)	(1.52)	(0.66)	(1.65)	(0.89)
Post-estimation test:				
$Post_{p,t} + Post_{p,t} * ACC_a$	-0.186	-0.233	-0.159	-0.215
(accounting anomalies)				
Mean of Dependent Variable	0.256	0.182	0.300	0.225
	Panel B: Falsification Test			
$Post_{p,t}$	-0.176	-0.829*	-0.272	-0.422
(non-accounting anomalies)	(-0.50)	(-1.92)	(-0.59)	(-0.75)
$Post_{p,t} * ACC_a$	0.659	1.056**	0.684	0.494
(difference in difference)	(1.63)	(2.21)	(1.23)	(0.77)
Post-estimation test:				
$Post_{p,t} + Post_{p,t} * ACC_a$	0.483	0.227	0.412	0.072
(accounting anomalies)				
Mean of Dependent Variable	0.464	0.172	0.556	0.235

Table IX
Drop annual sibling, thin portfolios

This table presents the coefficients from the robustness tests of the baseline difference-in-difference regression results reported in Table II. Panel A features a modified sample of anomalies. We first identify the 23 sibling anomalies in our sample of 205 anomalies, that is, pairs of anomalies that exploit the same investment idea, but have portfolios formed based on annual signals and quarterly signals, respectively. We then drop the 23 annual siblings and estimate Equation (1) on the sample of 183 anomalies in the period from January 1992 to December 1997. Panel B features a full sample of 205 anomalies in the period from January 1992 to December 1997, with observations removed from the sample if the portfolio construction of either the long leg or the short leg for a given anomaly in a given implementation phase was based on thin portfolios, that is, portfolios consisting from fewer than five stocks. $Post_{p,t}$ is an indicator equal to one if month t is on or after the implementation date for phase p, and equal to zero if month t is before that date; ACC_a is an indicator variable that equals one if a is an accounting anomaly, and equals zero if a is a non-accounting anomaly. The dependent variables $\widehat{\alpha_{a,p,t}}$ in the four columns of the table are the Fama-French six-factor alphas for quintile (1-5) or decile (1-10), equal-weighted (EW) or value-weighted (VW) portfolios. The portfolio alphas and the coefficients are expressed in percentages. All specifications contain anomaly and month fixed effects. The standard errors are clustered by anomaly and by month to address the potential correlation in errors. Robust t-statistics are presented in parentheses below the estimates. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	FF6 Alpha 1-5 EW	FF6 Alpha 1-5 VW	FF6 Alpha 1-10 EW	FF6 Alpha 1-10 VW
	Panel A: Excluding Annual Siblings			
$Post_{p,t}$	-0.070	-0.049	-0.136	-0.140
(non-accounting anomalies)	(-0.68)	(-0.40)	(-1.09)	(-1.02)
$Post_{p,t} * ACC_a$	-0.424***	-0.419***	-0.439***	-0.508***
(difference in difference)	(-3.77)	(-3.52)	(-3.43)	(-3.57)
Post-estimation test: $Post_{p,t} + Post_{p,t} * ACC_a$ (accounting anomalies)	-0.494***	-0.468***	-0.575***	-0.648***
Mean of Dependent Variable	0.256	0.182	0.300	0.225
	Panel B: Excluding Thin Portfolios (with < 5 stocks)			
$Post_{p,t}$	-0.214**	-0.181	-0.169	-0.141
(non-accounting anomalies)	(-2.38)	(-1.65)	(-1.56)	(-1.07)
$Post_{p,t} * ACC_a$	-0.223**	-0.240**	-0.269**	-0.312**
(difference in difference)	(-2.13)	(-2.19)	(-2.20)	(-2.26)
Post-estimation test: $Post_{p,t} + Post_{p,t} * ACC_a$ (accounting anomalies)	-0.437***	-0.421***	-0.438***	-0.453***
Mean of Dependent Variable	0.464	0.172	0.556	0.235

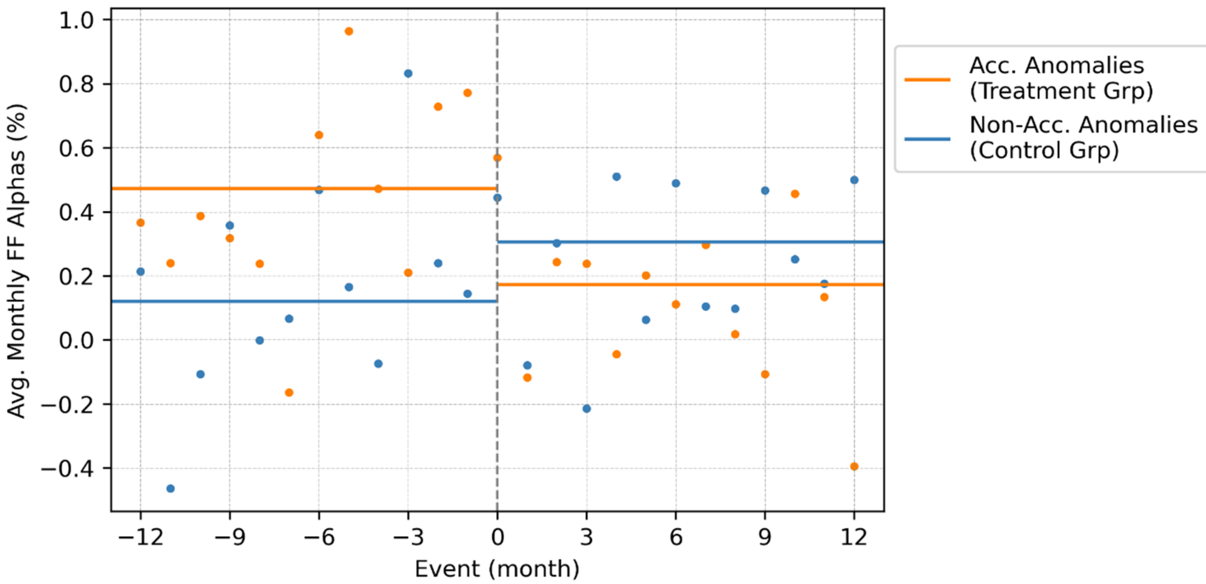

Figure 1: Attenuation of Accounting-based Anomaly Profitability in Response to EDGAR Implementation

This figure shows the changes in average monthly Fama-French six-factor alphas for the accounting-based anomaly portfolios in response to the staggered EDGAR implementation. The two orange horizontal lines represent the pre-EDGAR period versus the post-EDGAR period average alphas of the accounting anomaly portfolios constructed with EDGAR filers over the sample period with respect to the ten EDGAR implementation phases. Similarly, the two blue horizontal lines show the pre-EDGAR period versus the post-EDGAR average alphas of non-accounting anomaly portfolio consisting of EDGAR filers (the control group) over the sample period with respect to all implementation phases. The grey vertical dotted line in the middle represents the effective dates for implementation phases 1 (CF-01) through 10 (CF-10). The sample period is from January 1992 to December 1997.

Appendix A
Table A.I
Baseline Difference-in-Difference by Implementation Phase

This table presents the coefficients from the difference-in-difference anomaly portfolios regression similar to that from Equation (1). The estimated specification features additional interaction terms of the form $Post_{p,t} * ACC_a$* Phase i, where i = 2, 3/4, 5, 6, 7, 8, 9, 10, thus enabling the estimation of the difference-in-difference coefficient separately for each phase (implementation phase 3 (CF-03) has the same effective date as implementation phase 4 (CF-04)). $Post_{p,t}$ is an indicator equal to one if month t is on or after the implementation date for phase p, and equal to zero if month t is before that date; ACC_a is an indicator variable that equals one if a is an accounting anomaly, and equals zero if a is a non-accounting anomaly. The dependent variables $\widehat{\alpha_{a,p,t}}$ in the four columns of the table are the Fama-French six-factor alphas for quintile (1-5) or decile (1-10), equal-weighted (EW) or value-weighted (VW) portfolios. The sample extends over 205 anomalies in the period from January 1992 to December 1997. The portfolio alphas and the coefficients are expressed in percentages. All specifications contain anomaly and month fixed effects. The standard errors are clustered by anomaly and by month to address the potential correlation in errors. Robust t-statistics are presented in parentheses below the estimates. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	FF6 Alpha 1-5 EW	FF6 Alpha 1-5 VW	FF6 Alpha 1-10 EW	FF6 Alpha 1-10 VW
$Post_{p,t}$	0.0136	-0.0682	0.0466	-0.150
	(0.07)	(-0.29)	(0.20)	(-0.49)
$Post_{p,t} * ACC_a$	-0.286	0.0492	-0.371	0.154
	(-1.54)	(0.21)	(-1.60)	(0.52)
$Post_{p,t} * ACC_a$* Phase 2	-0.0612	-0.283	0.119	-0.363
	(-0.30)	(-1.01)	(0.46)	(-1.09)
$Post_{p,t} * ACC_a$* Phase 3/4	0.228	-0.172	0.340	-0.204
	(1.18)	(-0.65)	(1.21)	(-0.57)
$Post_{p,t} * ACC_a$* Phase 5	0.115	-0.0802	0.211	-0.241
	(0.48)	(-0.25)	(0.68)	(-0.60)
$Post_{p,t} * ACC_a$* Phase 6	-0.141	-0.487	-0.107	-0.939**
	(-0.49)	(-1.38)	(-0.28)	(-2.11)
$Post_{p,t} * ACC_a$* Phase 7	-0.462	-1.075**	-0.569	-1.588***
	(-1.22)	(-2.52)	(-1.29)	(-3.31)
$Post_{p,t} * ACC_a$* Phase 8	-0.835*	-0.664	-0.789	-0.855
	(-1.67)	(-1.12)	(-1.18)	(-1.24)
$Post_{p,t} * ACC_a$* Phase 9	-0.489	-1.279***	-0.637	-1.456**
	(-1.16)	(-3.04)	(-1.10)	(-2.51)
$Post_{p,t} * ACC_a$* Phase 10	0.263	-0.611*	0.445	-0.506
	(0.99)	(-1.78)	(1.18)	(-1.07)
Mean of Dependent Variable	0.327	0.253	0.358	0.304