RegTech: Technology-Driven Compliance and its Effects on Profitability, Operations, and Market Structure*

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Abstract

Compliance-driven investments in technology—or "RegTech"—are growing rapidly. To understand the effects on the financial sector, we study firms' responses to new internal control requirements. Affected firms make significant investments in ERP and hardware. These expenditures then enable complementary investments that are leveraged for noncompliance purposes, leading to modest savings from avoided customer complaints and misconduct. IT budgets rise and profits fall, especially at small firms, and acquisition activity and market concentration increase. Our results illustrate how regulation can directly and indirectly affect technology adoption, which in turn affects noncompliance functions and market structure.

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1. Introduction

In their compliance efforts, financial institutions (FIs) are increasingly investing in information technology and hiring technological experts, a development that industry participants refer to as “RegTech.” FIs spent over $30 billion on RegTech in 2020, and 2025 forecasts exceed $130 billion (Juniper 2022). RegTech investments commonly involve sweeping improvements in data collection and information systems. While regulators may intend for these improvements to enhance investor protection, FIs report also using RegTech investments in their operations management and strategy (Thomson Reuters 2021). Additionally, interactions among regulation, big data, and market power are attracting attention from researchers and policymakers concerned with compliance burdens, financial sector concentration, and financial service quality (Philippon 2016).

Despite growing interest in financial technology, we lack evidence on firms’ RegTech investments and their effect on operations and market structure. Few settings permit researchers to observe technological investments at individual firms. When data are available, studying technology adoption is inherently difficult: adoption decisions are typically endogenous, and in cases where adoption is driven by regulation, one must be able to observe both affected and unaffected firms.

In this paper, we use new internal control requirements for a subset of U.S. broker-dealers (BDs) as a setting that allows us to observe firms’ RegTech investment response. After first describing the nature and extent of compliance investments, we turn to our main focus: investigating the broader consequences for the financial sector by examining changes in affected firms’ profitability, noncompliance investments, and operations, as well as the structure of the market. To do so, we assemble a novel dataset covering multiple aspects of technological investment and operations at both affected and unaffected BDs. We track software and hardware investments using the Aberdeen Computer Intelligence Database, website technology adoption using BuiltWith, and technology-related labor demand using Revelio. For operations, we examine customer complaints and misconduct involving individual employees, publicly reported on the BrokerCheck website. BDs with available data account for the majority of the assets and employment in the industry and include both publicly and privately held FIs.

Our findings are as follows. We begin by showing that BDs affected by the new requirements made significant investments in enterprise resource planning (ERP) software and servers that directly aid compliance. IT budgets rose and profits fell, particularly at small BDs. These initial results provide context for investigating broader financial sector consequences. First, we show that compliance investments can indirectly affect technology adoption. Intuitively, by compelling information systems investments that can be leveraged for noncompliance purposes, regulation enables the adoption of communications and customer relationship management (CRM) tools that require high-quality information systems. Second, as a result of these technological investments and the ensuing information environment improvement, affected BDs saw fewer customer complaints and less employee misconduct. Finally, with cost structure changes and the scalable benefits of improved data, we find acquisition activity and market concentration increased.

The regulatory changes we study followed the discovery of large Ponzi schemes in the late 2000s, when the SEC sought to improve safeguards for BD custody of customer securities and funds. Accordingly, the 2014 amendments to Securities Exchange Act Rule 17a-5 (henceforth Rule 17a-5 or "the amendment") require certain BDs to report on their internal controls over compliance with rules concerning capitalization and separation of customer and firm assets.

Specifically, BDs must maintain controls for and documentation demonstrating *moment-to-moment* compliance with requirements to hold adequate net capital and segregate customer assets. Requirements of this sort are common in the financial sector, and the recent FTX failure has drawn additional attention to their design. While the amendment mandates internal control attestation only for carrying BDs—those that maintain custody of customer assets—all BDs must publicly disclose financial information, employee records, and complaint and misconduct details, providing a control group for our analyses.

Before the amendment, many carrying BDs used “systems and technology that have been built in-house many years ago… and as a result, have found it difficult to provide report logic details and report parameters to their auditors for testing” (Deloitte 2015). After the amendment, carrying BDs began to “invest in shoring up technology or data architecture to alleviate data-related concerns, including rationalizing data sources and centralizing data into a single data source… [thus establishing] increased accuracy and completeness of source data” (EY 2019).

Our first analyses describe the nature and extent of compliance-driven expenditures in the eight years around the amendment using tests with BD and location-by-year fixed effects and an extensive set of size and business model controls. We show that, after the amendment, carrying BDs were 16% more likely to add ERP software for the first time—notable because implementing an ERP system consumes significant time and resources. Carrying BDs also employed 19% more servers and increased technology-based compliance jobs by over 10%.

In the years following these investments, IT budgets grew by 24% and profits declined by 14%.[1] However, these effects are not uniform across BDs. Profits decline most among those with

[1] See also Labro and Stice-Lawrence (2020), who find evidence that regulation-driven accounting system updates impose significant costs on U.S. hospitals.

less sophisticated technology in the pre-amendment period, and smaller BDs worst positioned to absorb the fixed costs associated with major technological investments.

Building on these initial analyses, we investigate the broader consequences of RegTech, beginning with complementary investment. This analysis is motivated by theoretical research highlighting the non-rivalrous nature of data and information systems: multiple corporate functions can simultaneously use them without detracting from their compliance role (Jones and Tonetti 2020). Because of this nonrivalrous property, RegTech investments that improve a firm's internal information environment can increase the return on complementary assets (Teece 1986; Brynjolfsson and Hitt 2000; Hughes and Morton 2006). For example, by enhancing the monitoring environment, communication management tools can help BDs improve customer service and reduce the scope for complaints and misconduct. However, adopting these tools requires first having adequate information system quality. From this perspective, RegTech investments can render the necessary expenditures on these input factors sunk, and gains from complementary investments can partially offset the RegTech investment cost.

Consistent with this hypothesis, we find that carrying BDs were more likely to implement communication management programs following the amendment. We also observe significant adoption of CRM and premium website technologies commonly linked to internal analytics tools and data infrastructure.[2]

To understand the operational effects of these technological investments, we then examine customer complaints and employee misconduct after the amendment. Common incidents relate to unsuitable investment recommendations, excessive trading, and commissions—grievances unrelated to the amendment itself but conceivably reduced by monitoring via the BD's internal

[2] As examples, ThreatMetrix provides real-time fraud detection and transaction security, Pardot automates marketing and sales engagement, and goMoxie allows live chat between the customer and BD.

information processes. At carrying BDs, the complaint and misconduct incident likelihood declined by four percentage points. We find no evidence that these effects were driven by business model differences or other regulation including Dodd-Frank.[3] We also find little indication that regulator or auditor attention explain the decline, although we acknowledge that measuring attention is difficult.

Instrumental variable tests point to the complaint and misconduct declines happening through the technological investments studied in our earlier analyses. In additional tests examining the onset of COVID-19 as a natural experiment, we further establish a role for technology in improving customer service. COVID-19 forced most BD employees to work remotely, and we find BDs with superior technology beforehand were better positioned to avoid customer complaints amid the significant market turmoil.

Despite potentially benefitting from complaint declines, the damages BDs avoided are modest, and for the smallest BDs, represent under one-tenth of their IT budget increase that followed the amendment. This evidence raises questions about the market structure consequences of RegTech, which we explore in our final tests.

RegTech can affect market concentration through the relative burden of compliance costs and the differential benefits of additional data. SEC comment letters discuss how the amendment's compliance costs have a sizable fixed component and how larger BDs can more easily bear them (SEC 2013). In terms of benefits, large FIs use more hard information in their operations (Stein 2002). We find the amendment significantly increased market concentration among carrying BDs, and we link this to heightened acquisition activity and labor flows. The social welfare effects of RegTech and concentration are complex (Carlton 2007; Covarrubias, Gutierrez, and Philippon

[3] More generally, we note that back-office differences in carrying and noncarrying BDs have little to do with the customer complaints we study.

2020), and studying them is beyond the scope of our paper. Nevertheless, our evidence illustrates how regulation that compels technology-driven compliance can affect market structure.

We make three contributions. By offering the first empirical analysis of RegTech, we add to the growing literature on technology adoption at FIs (D'Acunto, Prabhala, and Rossi 2019; Crouzet, Gupta, and Mezzanotti 2023; He et al. 2021; Higgins 2022; Kwan et al. 2022; Liberti, Sturgess, and Sutherland 2022; Pierri and Timmer 2022) as well as the broader FinTech literature (Buchak et al. 2018; Fuster et al. 2019; Begenau, Farboodi, and Veldkamp 2018). FIs increasingly rely on technology to demonstrate compliance with reporting, capital, consumer protection, and risk management regulations (Deloitte 2021). We illustrate how regulation can both directly and indirectly affect technology adoption. The direct effect manifests as significant improvements in data collection and information systems made for compliance purposes. The indirect effect stems from these improvements rendering sunk the data infrastructure and information quality required to adopt complementary software and CRM tools in noncompliance functions.

Second, we add to the literature on complaints and misconduct at BDs (Dimmock and Gerken 2012; Charoenwong, Kwan, and Umar 2019; Egan, Matvos, and Seru 2019, 2022; Kowaleski, Sutherland, and Vetter 2020). Complaints are relevant to trust and participation in the financial system (Guiso, Sapienza, and Zingales 2008; Giannetti and Wang 2016; Gurun, Stoffman, and Yonker 2018), have resulted in billions of dollars of settlements over the past decade, and are a major focus of BDs' risk management. One challenge in monitoring complaints is that the advisory business is relationship-based (Dimmock, Gerken, and Van Alfen 2021; Gurun, Stoffman, and Yonker 2021), and individual employees have discretion in advising clients. We document a role for technology in improving financial service quality by enhancing employee monitoring. (See also Bachas et al. 2018; Heese and Pacelli 2022.) The associated savings we find, however, appear *far smaller* than the total technology implementation costs, indicating that investment complementarities are important to facilitating adoption.

Finally, we add to research exploring direct and indirect benefits from improving internal controls and the information environment in response to regulation (e.g., Feng, Li, and McVay 2009; Ellul and Yeramilli 2013; Baxter et al. 2013; Feng, Li, McVay, and Skaife 2015; Gallemore and Labro 2015; Shroff 2017; Miller, Sheneman, and Williams 2022; Schoenfeld 2022). One implication of our findings is that technological advances creating new opportunities for data collection and monitoring will strengthen the linkages across compliance and noncompliance functions that depend upon customer and employee data.

2. Broker-Dealers and the Rule 17a-5 Amendments

2.1 U.S. Broker-Dealers

BDs trade securities for themselves and their customers. Their customers include individual households and institutions that invest in debt, equities, mortgage-backed securities, mutual funds, options, variable life insurance, and other securities. According to FINRA's industry snapshot (FINRA 2022), as of 2021, there were over 610,000 registered employees, with 182 (12) at the average (median) BD. There are 3,394 registered BDs with nearly 150,000 branches, generating over $390 billion in revenue and $90 billion in income.

A key characteristic distinguishing BDs is whether they maintain custody of (or "carry") customer assets. Carrying BDs face tighter regulation because their direct control over customer assets creates opportunities for misappropriation and loss. To avoid this regulation, a noncarrying BD (or an "introducing" BD) must promptly transmit any customer assets it receives to another BD. Though carrying and noncarrying BDs both have customer-facing representatives, only carrying BDs have the back-office custodial function that is affected by the regulatory change we study.[4] Economies of scale and having compliance expertise are amenable to being a carrying BD: carrying BDs tend to be large, and switching between carrying and noncarrying status is exceedingly rare. Roughly 5% of BDs are carrying BDs.

Carrying and noncarrying BDs offer similar fee schedules to customers, typically based on the customer's portfolio size and trading frequency. Most customers are likely unaware of the distinction—it is difficult to find references to the BD's carrying status on their website or advertisements, for example. Instead, the websites typically promote the quality of advice provided, relationship building, and information about products and locations.

2.2 Rule 17a-5 amendments and the regulatory environment

BD reporting is regulated under Rule 17a-5 of the 1934 Securities Exchange Act. Each year, BDs must furnish audited reports containing financial statements and accompanying regulatory schedules and reports. In 2014, the SEC amended Rule 17a-5 to increase focus on the regulatory schedules and reports. The amendments were made following the failure of the carrying BD MF Global, which exposed customer asset custody and segregation issues that are difficult for unsophisticated investors to monitor.

The amendment's Financial Responsibility Rules seek to manage the risk of customer losses from unexpected BD failures in several ways. First, BDs must maintain a minimum level of safe and liquid assets to cover firm obligations.[5] Second, BDs must segregate customer from firm

[4] Maintaining custody and clearing trades allows a BD to keep more of the fees charged to their customer rather than outsourcing custodial requirements and sharing fees with another BD. The largest carrying (noncarrying) BDs have over 10,000 employees, and include American Enterprise Investment Services Inc, Charles Schwab & Co., and Wells Fargo Clearing Services (PFS Investments Inc., Susquehanna Securities, and Wealth Enhancement Brokerage Services LLC). The smallest carrying (noncarrying) BDs have just a handful of employees, and include Koonce Securities LLC and Marsco Investment Corporation (Cooper Malone McClain, Inc. and Diamant Investment Corporation).

[5] This requires BDs to document the investment haircuts and operational charges that reduce net assets when computing Net Capital, the aggregate indebtedness that raises the minimum required Net Capital, and the reliability of systems that produce the information.

assets. Third, BDs must perform a periodic security count to affirm company records and send account statements to customers. Additionally, the amendments newly require managers at carrying BDs to state that they have established and maintained internal controls that provide reasonable assurance that noncompliance with the Financial Responsibility Rules will be prevented or detected on a timely basis.

Separate from Rule 17a-5, BDs also face oversight from the Financial Industry Regulatory Authority (FINRA), a self-regulatory enforcement agency tasked with protecting investors. FINRA develops and enforces rules, conducts onsite exams, oversees firm and employee licensing, and maintains a website, "BrokerCheck," with profiles for every registered employee. The website includes each employee's licenses, registration status, employer (current and past), and detailed records of customer complaints, civil proceedings, and regulatory sanctions.

Complaints can be reported by customers, regulators, or the BD. The most common incidents involve unsuitable investment recommendations (21% of incidents), misrepresentation (18%), unauthorized activity (15%), omission of key facts (12%), commission-related issues (9%), and investment fraud (8%) (Egan et al. 2019); these categories are not mutually exclusive. This means the complaints we study relate to employee-customer interactions and not firm issues of custody, capitalization, and regulatory reporting affected by the amendments. Indeed, under the Securities Exchange Act, financial statement auditors are neither tasked with nor liable for oversight of customer complaints unrelated to financial reporting, at BDs or other businesses like restaurants or retailers.[6]

2.3 Technological investment

2.3.1 RegTech

[6] To confirm this, we reviewed LexisNexis for litigation against BD auditors. We found only two cases over the past 43 years involving the type of complaints we study.

BDs made significant expenditures to comply with the amendment, including ERP implementations and hardware investments (EY 2019; Palaparthi and Sarda 2020). ERP implementations in particular are known to be among the most costly and difficult IT projects that FIs undertake. Industry publications and consulting guides suggest a typical ERP adoption spans approximately a year. Delays and cost overruns are quite common: "As fundamental as they are, three-fourths of ERP transformation projects fail to stay on schedule or within budget, and two-thirds have a negative return on investment" (McKinsey 2019). Similarly, respondents to a recent FI survey report that RegTech implementations involve significant budget needs and efforts to upgrade employee skillsets (Thomson Reuters 2021). Overall, despite producing some side benefits associated with the improved information environment, the RegTech implementations following the amendment involved significant costs, and we expect most FIs view them as mandatory rather than voluntary.

In addition, during implementation, the systems are not fully functional. Accordingly, because the amendment passed in 2013 and took effect for carrying BDs with fiscal years ending on or after June 1, 2014 (most BDs have December 31 fiscal year ends), we expect investments to begin in 2013 or 2014 and any complaint decline to appear a year later.

2.3.2 Complementary investment

One way for FIs to offset, albeit incompletely, the burdensome compliance investments is through complementary software and website investment. Adopting an ERP system opens up the possibility of adding other communication and marketing tools that leverage the improved information environment. For example, we would not expect BDs to adopt ERP solely for the purposes of adding these tools, but the amendment effectively renders the ERP cost sunk. For BDs, there are several technological applications that monitor employees' interactions with customers and identify problematic behavior that results in costly complaints or misconduct. As one example, a recent FINRA white paper (FINRA 2018) explains:

> Some [software] tools that seek to employ a more predictive risk-based surveillance model also focus on linking data streams previously viewed largely in isolation. For instance, the relationship between certain structured data (such as trade orders and cancels, market data, and customer portfolio) and unstructured data (such as emails, voice recordings, social media profiles and others [sic] communications) have historically been difficult to link together. However, [software] tools are being developed that would help to integrate these disparate data forms and then identify and track related anomalies that merit attention (p. 4).

3. Empirical Methodology

3.1. Data and measures

We construct our sample from the intersection of several datasets. BD-level registration data (Form BD) come from FINRA, and BD customer complaints and employee data come from BrokerCheck. We obtain our baseline BD-year panel using the Audit Analytics Broker-Dealer module, which assembles all annual Rule 17a-5 reports filed with the SEC. Into this dataset, we merge the BrokerCheck complaint and employee data. The sample for our complaint analysis, after accounting for all controls and sample filters, includes 3,086 unique BDs and 17,810 BD-year observations between 2010 and 2017. Our technology adoption analysis samples contain fewer observations, depending on data coverage in Aberdeen, BuiltWith, and Revelio. Appendix A.1 describes the merging procedures, sample restrictions, and data coverage for each sample. As Figure A.1 illustrates, coverage is better for the larger BDs. Thus, although these datasets cover just over half of sample BDs, in terms of total assets or headcount our tests cover a large majority of the market, aiding the generalizability of our findings.

We identify carrying BDs using financial and registration data reported in 2015. We first ensure that the BD reports a required minimum level of Net Capital of at least $250,000.[7] Because other circumstances may require noncarrying BDs to maintain net capital exceeding this amount, we then review data filed under Form BD to identify BDs that report clearing trades for other BDs as well as those that report introducing arrangements.[8] We use this information to distinguish between carrying and noncarrying BDs, and validate our approach using public and administrative sources.

Table 1, Panel A reports summary statistics for all BDs in our sample.[9] The mean (median) BD has approximately $1.26 billion ($668,000) of assets and $648 million ($293,000) of net capital.[10] Carrying BDs comprise 5.4% of our sample, and 47.4% of our observations are from the *Post* period. The mean (median) BD has 211 (11) adviser and representative employees, with an average tenure of 6.2 years. On average, 29.4% of employees are dually registered as investment advisers, and 4.5% of employees have a complaint on their record. Appendix A.2 reports separate figures for carrying and noncarrying BDs; the largest raw differences relate to size. Later, we describe how our matching analyses and robustness tests account for such differences. The probability of a BD receiving any complaints in a year is 9.9%, while the probability of a customer-reported misconduct incident is 7.5%.

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[7] SEA Rule 15c3-1(a)(2) requires BDs that carry customer or BD accounts to maintain net capital of not less than $250,000.

[8] For each BD that reports minimum required Net Capital of $250,000 in 2015, we check the following. If a BD reports that it "Clears for other BDs," we code *Treated* as one. If not, we only code *Treated* as one when the BD reports that it does not engage in any of the following introducing arrangements: 1) refers or introduces customers to any other broker or dealer; 2) has an arrangement with any other person, firm, or organization under which any books or records of applicant are kept or maintained by such other person, firm or organization; 3) has an arrangement with any other person, firm, or organization under which accounts, funds, or securities of the applicant are held or maintained by such other person, firm, or organization; or 4) has an arrangement with any other person, firm, or organization under which accounts, funds, or securities of customers of the applicant are held or maintained by such other person, firm or organization.

[9] These full sample statistics may differ from those reported in our regression tables as the samples may differ due to merging, singletons, control variable availability, and winsorization.

[10] Assets refers to the BD's own assets and not Assets under Management, which are not publicly available.

3.2. Research design

Our empirical analyses use the following specification:

$$y_{i,t} = \alpha_i + \alpha_{f(i,t),t} + \beta \times Post_t \times Treated_i + \Gamma' \times X_{i,t-1} + \varepsilon_{i,t}, \quad (1)$$

where i indexes BDs, t indexes years, and $f(i,t)$ is the FINRA district for BD i during year t. The sample period spans 2010 to 2017. The dependent variable measures RegTech investments, complementary investments, customer complaints, employee misconduct, or acquisitions as described in subsequent sections. For count variables (e.g., the number of servers or jobs) we use a Poisson estimation (Cohn, Liu, and Wardlaw 2022); otherwise we use OLS or fractional response regressions as labeled.[11]

$Post$ is an indicator variable equal to one beginning in 2014. $Treated$ is an indicator variable equal to one for carrying BDs and is static within each BD.[12] Thus, β captures the investment, complaint, or misconduct difference between carrying and noncarrying BDs caused by the amendment. α_i are BD firm fixed effects that account for time-invariant BD features, including the business model and customer base. $\alpha_{f(i,t),t}$ are FINRA district-by-year fixed effects that account for local economic conditions as well as time-location level enforcement variation.[13] The BD firm and FINRA district-by-year fixed effects absorb the *Treated* and *Post* main effects, respectively. Our control variables $X_{i,t-1}$ consist of the previous fiscal period's ending log total assets, the fraction of employees with a previous complaint, the log average BD employee tenure,

[11] Our inferences are similar if we use OLS with dependent variable transformations (e.g., inverse hyperbolic sine or logarithmic) rather than a Poisson specification.

[12] Our discussions with regulators and market participants and our review of industry publications finds that switching between carrying and noncarrying status is quite rare in general. This appears intuitive as switching from one status to the other requires a costly transition from proprietary back-office infrastructure to that of a new custodian, with whom the BD must now share fees.

[13] There are 11 FINRA districts, named for the location of their primary office: San Francisco, Los Angeles, Denver, Kansas City, New Orleans, Dallas, Atlanta/Boca Raton, Chicago, Philadelphia/Woodbridge, Long Island/New York, and Boston.

cubic controls for number of employees, and the fraction of employees who are dually registered as investment advisers. We include these lagged control variables to account for business model factors (size in particular) that are correlated with investment and complaints, but our inferences are similar if we omit controls.[14] We also include a separate linear time trend for investment advisers, given they offer different services than brokers (they are licensed to provide investment advice) and face additional regulation (Charoenwong et al. 2019). We winsorize all continuous dependent and independent variables at the 1% level, and cluster standard errors by BD. We present event study plots for our key regression results in Figure 1.

4. Empirical Results

4.1 Technology adoption

4.1.1 RegTech

We study BDs' RegTech investments in software, hardware, and personnel. We access Aberdeen's Computer Intelligence Database ("CiTDB"), which has been used to study digitization and technology adoption (Bloom, Sadun, and Van Reenan 2012; Bloom et al. 2014; Graetz and Michaels 2018; He et al. 2021; Kwan et al. 2021; Tuzel and Zhang 2021; Heese and Pacelli 2022; Pierri and Timmer 2022). Aberdeen collects data from several sources. Each year, they survey senior IT executives about software and hardware usage. Additionally, they conduct systematic data collection efforts, including web-scraping job postings and purchasing customer lists from vendors to identify software choices.

Our analyses use two CiTDB datasets. The first reports firm-level software usage categorized by type, allowing us to study specific software investments around the amendment, as proxied by the adoption of a new software type. The second dataset tracks and estimates the total

[14] Table A.2 presents results without controls.

IT budget for software, hardware, and staff across over 3 million establishments. Specifically, Aberdeen combines survey responses on budgets and hardware and web-scraped data with imputed values based on Dun & Bradstreet figures on firm age, industry, revenue, employment, and location. During our sample window, we can match 7,694 BD-year observations to the software dataset and 18,313 BD-year observations to the hardware dataset.

The RegTech software investments that we consider include ERP tools that enable the firm to develop, maintain, and report the information required to demonstrate moment-to-moment compliance with Rule 17a-5. Specifically, ERP allows for automation and better audit trails. Firms with ERP systems can quickly generate financial reports, monitor and control which employees access data, and reduce or eliminate reliance on manual work that leads to delays, errors, and fraud. ERP software also integrates a company's financials, reporting, operations, and human resource activities. For this reason, ERP is often referred to as the central nervous system of a business.

To study labor demand, we gather data from Revelio. Revelio collects labor data from a variety of sources, including professional networking websites, job postings, employee reviews, and H1-B visa filings. This dataset allows researchers to track the number of jobs by role based on skill categories over time at a large set of firms (see also Li et al. 2022). We classify RegTech jobs at BDs based on the fraction of employees whose listed skills include the terms "data," "software," "databases," "audit," "compliance," "risk management," or "internal controls." We further categorize RegTech jobs as tech-based if they include the first three of these skills and compliance-based if they include the last four (the two job types are not mutually exclusive). Our final matched BD-Revelio sample with nonmissing controls includes 13,766 BD-year observations.

Summary statistics for these variables are reported in Table 1, Panel B. For context, the median BD with nonmissing data in the software (IT budget and hardware) sample has 37 (19) employees (dataset coverage favors larger BDs, as shown in Figure A.1). Of the BDs without ERP in the pre-amendment period, the annual probability of adopting ERP in the post-amendment period is 12.7%. Of the BDs with ERP in the pre-amendment period, 87.9% of them add an additional ERP program in the post-amendment period. (While a firm generally has one ERP *system*, firms occasionally have multiple ERP *programs*, for example, because tools and functionality differ across programs, program offerings evolve, and business segments of the same firm can have different needs). The median BD has six servers and an IT budget of approximately $450,000. At the typical BD, around 10% of workers have a RegTech role, 5.1% have a tech-based RegTech role, and 4.7% have a compliance role. The latter figure is comparable to Trebbi and Zhang (2022), who study a longer sample period and broader set of FIs and regulations and find that over 3% of FIs' wage bill relates to regulatory compliance.

Table 2 models RegTech investments and labor demand using Equation (1). Column 1 studies how many BDs adopt ERP for the first time (i.e., the extensive margin), and finds a 16.3% greater increase for carrying BDs in the post-amendment period. For context, almost 60% of carrying BDs did not have ERP in the pre-amendment period, and by 2017, 22% of this group adopt. Column 2 examines BDs already having ERP in the pre-amendment period. We find an insignificant increase in the number of ERP software programs BDs employ (the intensive margin). Thus, in terms of software, the amendment's primary effect was to cause many carrying BDs to adopt ERP for the first time.

The remaining Table 2 columns study RegTech hardware and labor demand. Column 3 uses a Poisson specification, and finds an approximate 19% increase in the number of servers for carrying BDs.[15] For labor demand in columns 4-6, we employ a fractional response regression

[15] We find a comparable increase if we scale the number of servers by pre-amendment levels or by employee count.

(e.g., Papke and Wooldridge 2008; Dorta 2016), as our dependent variable is the share of the BD's total jobs that relate to each RegTech job category. Column 4 finds that carrying BDs increase overall RegTech jobs. Column 5 shows a significant increase in technology-focused roles, and column 6 shows an insignificant increase for traditional compliance roles.[16] Based on the average marginal effects from our fractional response regression, carrying BDs increase the share of RegTech (Tech-based RegTech) jobs by nearly one-tenth (one-sixteenth) of the mean. Thus our evidence corroborates claims from BDs, regulators, auditors, and vendors that the amendment compelled significant technological investments and hiring.

Next we assess the robustness of our technology adoption findings, focusing on BDs adopting ERP for the first time (i.e., the dependent variable in column 1 of Table 2). First, to more closely link the amendment to investment increases, Figure 1.1 models ERP investments in event time. The plotted coefficients are the difference between carrying and noncarrying BD investments yearly. We find a significant ERP adoption increase after the amendment, and parallel trends across carrying and noncarrying BDs before. A similar pattern emerges for servers and labor. This suggests that pre-trends or developments unrelated to the amendment do not explain the differential technological investment we document.

Second, carrying and noncarrying BDs may differ, for example, in their size or product offerings, and therefore their investments may have evolved differently, even absent the amendment. Thus, although we include a range of business model controls in Equation (1), the functional form may not fully account for the differences. Therefore, we conduct a matching analysis using subclassifications (Cochran 1968; Imbens and Woodridge 2009; Stuart 2010). Subclassification maps data to a propensity score and then stratifies them into different groups.

[16] Our results are similar using a Poisson or OLS specification.

Specifically, we construct the matched sample based on all control variables plus the number of product offerings, splitting continuous variables into 100 subclasses. Figure A.2 illustrates the raw and adjusted differences between treatment and control samples; the noticeable raw differences relate to assets and headcount, but the adjusted differences are small and none are statistically significant. Table A.3 shows that we find similar results, regardless of whether we retain all matches and only focus on within-subclass variation (column 1) or drop those with high treatment-control imbalances, defined as those with more than 100 control BDs for each treated BD (column 2).

Third, although we include cubic size controls, we further evaluate the possibility that size differences between carrying and noncarrying BDs could explain our results. Column 3 includes size-specific trends by interacting an indicator variable for BDs with above-median headcount with our *Post* variable. Not only do our results remain but also this interaction term is statistically and economically insignificant, suggesting that our results cannot be explained by larger BDs more aggressively adding ERP during our sample period or by data coverage favoring larger BDs. Similarly, our results remain if we eliminate the smallest and largest 1% or 5% of carrying and noncarrying BDs from our sample.

Fourth, in light of the numerous regulatory developments banks faced over the past decade (e.g., Dodd-Frank), column 4 drops bank affiliates without diminishing the effect. Our results also remain if we begin our sample in 2012 (column 5, Dodd-Frank passed in 2011); if we include separate year fixed effects for registered investment advisers (column 6), or if we omit BDs involved in mergers during our sample window (column 7).

Fifth, we repeat our tests using an alternative control group: U.S. banks.[17] If our RegTech investment results merely pick up a broader technology adoption trend in the financial sector, then we should find no difference between carrying BDs and U.S. banks. However, column 8 shows carrying BDs invest significantly more following the amendment.

4.1.2 Profitability

Table 3 studies the profitability implications of the amendment. We begin by tracking IT budgets in column 1. We find a 24% increase, in line with the amendment causing major ERP implementations, system upgrades, and hiring. Column 2 studies profitability, measured as the ratio of the current year's net income to average net capital in the pre-amendment period.[18] Profits decline by 14%, representing approximately one-third of the pre-amendment average. The event time plots in the bottom of Figure 1.1 show significant post-amendment profit and IT budget differences and little pre-amendment differences.

The remaining columns show these consequences are not uniform across BDs. The largest ones (defined as those with above the 90th percentile of headcount in the pre-amendment period) experience a statistically insignificant 4% IT budget increase. Meanwhile, IT budgets at smaller BDs (below the 90th percentile of headcount) grow significantly, by nearly 29%. Columns 5 and 6 show a similar pattern for profitability: there is little effect for large BDs, and a big decline for small ones.[19] Consistent with the profitability decline being driven by technology adoption, columns 7 and 8 find the decline is larger for BDs with less sophisticated technology in the pre-amendment period. Using alternative profitability measures (e.g., return on assets) produces a

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[17] Our specification includes cubic controls for lag headcount interacted with an indicator for whether the firm is a bank, and firm and state-year fixed effects.
[18] Financial statement information provided by LaRoche Research Partners, LLC.
[19] Note that Generally Accepted Accounting Principles allow investments in hardware and software to be capitalized and depreciated over time, rather than expensed immediately, resulting in a delayed effect on profitability.

similar pattern, as shown in Table A.4, as does employing other BD size thresholds (different levels of headcount or different bases such as Assets). Thus, the amendment's burden was much greater for smaller BDs, consistent with the associated compliance costs having a sizable fixed component.[20]

4.1.3 Complementary investments

We study two types of complementary technology adoption: software and website technologies. For software, we examine communication management programs in Aberdeen. Specifically, we record the presence of communications, web analytics, collaborate design & publish, advertising, live chat, website, and retail & digital tools that broadly relate to customer communications. Useful for our purposes of tracking complaint- and misconduct-relevant technologies, these tools support behavioral detection models to inform timely monitoring of employee conduct. For example, damages and sanctions resulting from customer complaints are increasingly issued based on email or other communications initiated by employees (e.g., phone, video, social media).[21] To avoid costly customer complaints, BDs can adopt communication programs that digitize records of employee communications, and document management tools that allow artificial intelligence-based analysis of collected data. Communications tools also aid advertising and customer outreach in ways that can improve service quality. Not only do each of these tools improve the information environment, but they also interface with and benefit from the more foundational ERP software examined in our RegTech tests. For example, ERP systems allow supervisors to access and monitor employee communications in combination with information about employee actions.

[20] Similarly, public comment letters warn that small BDs would be disproportionately harmed by the amendment, given the associated fixed compliance costs (SEC 2013).
[21] See https://www.smarsh.com/blog/must-know-finra-trends-the-impact-on-compliance/

Second, we collect data on website technologies from BuiltWith, a competitive intelligence firm that tracks technology adoption patterns (Koning, Hasan, and Chatterji 2022). BuiltWith regularly scrapes a substantial fraction of the internet, and each time it visits a webpage it logs the presence of a technology or tool. For example, BuiltWith may track whether a website uses a cookie to track visitors, has a chat function or transaction fraud prevention tool, or has integrated social media such as Twitter or Facebook. FIs commonly employ CRM website technologies to track user patterns and collect information about customers. These website technologies are often linked to the internal software programs mentioned above that help track communications, and other tools that perform risk and profitability analysis. CRM tools are also a key part of online portals, which are used by advisers to communicate with customers. In turn, the portals can help customers identify issues with, for example, securities they own, advice they have received, or commissions they are charged. Accordingly, we record when each BD adopts new CRM website technologies. We also measure the adoption of premium (i.e., paid for) website technologies. Premium website technologies commonly have a marketing focus but can require richer databases and better cybersecurity, webpage development, and overall infrastructure. Because website technologies evolve and old ones get removed when outdated (e.g., Adobe Shockwave or Microsoft Silverlight), we measure the extensive margin—whether the BD adopts a new technology that year. Collectively, these software tools and website technologies facilitate employee monitoring by both BDs and customers.

Table 4 studies complementary investments using equation (1). Column 1 finds that, following the amendment, carrying BDs are 3% more likely to adopt communications software. Similarly, column 2 finds an 11% increase in the probability that the BD adds CRM website technologies in a given year, and column 3 finds an 11% increase for premium website technologies.

One concern about our complementary investment results is that they are driven by omitted factors unrelated to the amendment. Therefore, column 4 conducts a placebo test, where we study investments in job applicant management and payroll software. We find no difference in carrying and noncarrying BD investments for this software type.

4.2. Customer complaints and employee misconduct

To understand the effects of technology adoption on operations, we study complaints and employee misconduct using Equation (1). Our measures are 100 times an indicator variable for whether the BD’s employees receive a customer complaint or have a customer-reported misconduct incident recorded that year. For complaints, following Charoenwong et al. (2019), we consider all types regardless of ultimate resolution. For misconduct, we follow Egan et al. (2019) and identify resolved incidents, focusing on customer-reported misconduct to avoid regulator attention-driven effects (see 4.2.1 for additional discussion).

Column 1 in Panel A of Table 5 shows that after the amendment, the complaint probability falls by 4.4% more for carrying BDs. Column 2 shows a 3.6% decline in the probability of a customer-reported misconduct incident, and column 3 shows a 4.3% decline in the number of incidents resulting in $5,000 or more of damages. Thus, technology not only improves customer service (as proxied by a decline in customer complaints), but also reduces costly misconduct.

Figure 1.2 presents event time plots based on columns 1 and 2. Complaints and customer-reported misconduct evolve similarly for the two types of BDs in the pre-amendment period and drop for carrying BDs starting in 2014. Recall from Figure 1.1 that carrying BDs’ ERP investments begin in 2013 and, from Section 2.3.1, that these types of investments can take a year or more.

Thus a sustained complaint and misconduct decline beginning in 2014 is consistent with the amendment causing major technological investments that ultimately aid monitoring.

We then trace the complaint and misconduct decline to technological investments using an instrumental variables analysis. Specifically, we construct an index, *Tech Index*, that encompasses the technological investments examined in our prior tests. First, we take the inverse hyperbolic sine of each of the number of servers, ERP software types, and CRM website technologies. Second, we take the Z-score of each of these three measures. Third, we average the Z-scores across the available measures for each BD. For example, a BD with a Z-score of 1 for the transformed server variable and 0.5 for the transformed CRM website technology variable but no available software data will have an index value of (1+0.5)/2 = 0.75.

Panel B presents the results. In the first stage, we find a significantly positive relation between *Treated* × *Post* and *Tech Index*, and the first-stage F-statistic is 35.7. Columns 2-4 then find that BDs making larger investments are significantly less likely to have complaints, misconduct, or financial damages resulting from a complaint.

The benefit of our approach is that it is holistic: it considers multiple aspects of BDs' technological expenditure response, while allowing us to develop a sufficient sample for an instrumental variables analysis. (Our Aberdeen and BuiltWith samples do not fully overlap, and our approach allows us to include BDs with partial coverage.) Nevertheless, we find similar results under a range of alternative approaches, including studying servers, labor demand, CRM technologies, or the IT budget alone, or employing a PCA estimation.

To put our findings in perspective, we collect data on financial damages associated with customer complaints. Damages are publicly disclosed in complaint filings, and can take the form of fines, sanctions, and settlements. We then compare the avoided damages (assuming a 5%

complaint decline based on our Table 5, column 1 coefficient) with the 29% IT budget increase shown in Table 3, column 4 for small BDs (large BDs saw only an insignificant increase). The budget increase outstrips the savings from avoided complaints by a factor of over 10. Of course, this is a simple exercise that requires us to abstract away from other considerations (e.g., reputation penalties). Although not definitive, this evidence complements our profitability tests by showing the savings from avoided complaints and misconduct are rather modest compared to the IT expenditures BDs undertake in response to the amendment.[22]

4.2.1 Additional evidence on complaints and technological investment

We cannot be certain that the exclusion restriction condition underlying our instrumental variables test is satisfied. Although the amendment focused on internal controls over compliance, it may have been enacted as part of a larger effort to improve customer protection and tighten enforcement across multiple aspects of BD operations. Then, the complaint decline could stem from heightened regulator or auditor attention and not technological monitoring (regulator or auditor attention could bias the IV estimation in favor of fewer complaints). Therefore, we conduct several additional tests exploring both attention and technology adoption.

First, we study regulator attention. We use Form BD filings to identify BD product offerings. We classify BDs as retail-focused if they offer investment advice, mutual funds, variable life insurance, or debt products. As retail investors are less sophisticated than institutional investors, FINRA focuses on protecting them from predatory BD sales tactics. Under a regulator

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[22] To further illustrate and link to our profitability findings, suppose customer tracking software costs F2, but using this software requires a firm to have ERP costing F1. The total cost of adopting the customer tracking software is F1 + F2. The marginal benefit from the customer tracking software is B, with F1 < B < F1 + F2. A firm without ERP does not invest because B < F1 + F2. However, if a firm incurs F1 for regulatory purposes, the marginal cost of purchasing the customer tracking software is now F2 < B. Overall, the profits will decline by F1 + F2 – B, which is less than if it had incurred F1 alone.

attention interpretation of Table 5, regulator-reported complaints should decline at retail-focused BDs, and the decline should vary with the BD's distance to the nearest FINRA office. However, columns 1-3 of Table 6 present a different pattern. Customer-reported complaints decline at retail-focused BDs, consistent with improved technology helping BDs monitor interactions between their employees and customers. Meanwhile, we see no change in regulator-reported complaints at retail-focused BDs, and these complaints appear insensitive to the distance between the BD and regulator.

We also consider whether regulation unrelated to Rule 17a-5 could explain the complaint declines. For example, banks had staggered deadlines for adopting provisions of Basel III. In column 4 of Table A.5, we drop all BDs that are bank affiliates or subsidiaries. Our results remain. Likewise, Dodd-Frank affects only a subset of BDs and our main specification controls for differential trends for them.[23]

Second, we examine auditor attention. Because audits are a credence good, reputation plays an important role in the audit market. The most reputable auditors avoid clients engaging in wrongdoing, even that which does not pertain to financial reporting (Cook et al. 2020). If our Table 5 results stem from auditor attention, then we expect the complaint decline to be concentrated in BDs whose auditors are least tolerant of wrongdoing. To test this, we interact *Auditor Tolerant*, an indicator for the BD's audit firm having an above-median proportion of clients (excluding the focal BD) with complaints in the pre-amendment period, with *Post* x *Treated*. The *Auditor Tolerant* measure is size-adjusted in that we first assign auditors to size terciles based on their number of

[23] Table A.5 investigates a variety of explanations related to BD business model differences. We find a complaint decline across a range of specifications that control for such differences via matching approaches, time-varying size controls, and subsample analyses.

clients in the same period. Column 4 of Table 6 shows an insignificant triple interaction coefficient, suggesting our results are not driven by auditor attention.

We conduct two additional tests exploring auditor attention. First, similar to column 3, we measure the distance between the BD and the auditor's office, given that monitoring is easier for closer auditors. Column 5 shows that the complaint decline does not depend on the auditor-BD distance. Second, some complaints involve employee behavior that might draw scrutiny from auditors and plausibly relate to their work. To investigate this, we build on Cook et al. (2020) and identify complaints with references to "churn," "embezzle," "forge," "fraud," "misappropriate," "stole," "unauthorized," "unregistered," and variants of these phrases (*Auditor-Related Complaints*). Approximately 10% of all complaints in our sample are *Auditor-Related Complaints*. Our assumption is that the amendment leads to more involved audits for affected BDs, and the nature and seriousness of complaints referencing forgery, fraud, and theft will draw extra auditor attention. Thus, under an auditor attention-based explanation, we should see starker declines in *Auditor-Related Complaints* than those involving behavior less relevant to auditors. However, Columns 6 and 7 of Table 6 show the opposite pattern: we find no economic or statistical change in *Auditor-Related Complaints* and a significant decline in *Non-Auditor-Related Complaints*.

Last, we use the onset of COVID-19 as a natural experiment that disrupted BDs' interactions with customers. COVID-19 forced most BD employees to work remotely, effectively shifting customer communications from the office (where they can be more easily monitored) to employees' homes. Technology can aid complaint oversight in such working conditions. Table A.6 presents the results. Column 1 shows that, in the post-COVID-19 period, BDs with better technology are significantly less likely to experience a complaint. Column 2 studies variation in the extent of work from home using the log number of COVID-19 cases in each county. For BDs with branches in multiple counties, we take the weighted average number of cases by weighting each location by the number of BD employees in the county.[24] We find technological investments reduce complaints most in counties with more cases. For context, the standard deviation of log cases is 5.2, so a one-standard-deviation increase in cases corresponds to a 0.84% (5.2 x 0.161) increase in the probability of a complaint. By comparison, a one-standard-deviation increase in *Tech Index* is 0.9, so a one-standard-deviation increase in the index corresponds to a nearly one-half reduction of this effect (-0.118 x 0.9/.161= -65%). Collectively, our evidence points to technological investment driving the Table 5 complaint and misconduct decline. However, regulator and auditor attention are difficult to measure and we cannot be certain that they do not play some role in the decline.

5. RegTech and Market Structure

Our final analyses investigate the interaction between the amendment and market structure. Our motivation is threefold. First, because technological investments have a large fixed component, the amendment's burden falls more heavily on smaller BDs. The SEC's summary of and response to public comment letters on the amendment illustrate this concern, describing how "the costs could disproportionately impact smaller broker-dealers due to the fixed cost components … of compliance with these requirements" (SEC 2013). Our profitability results support this claim.

Second, research illustrates how large FIs make greater use of hard information in their operations (Stein 2002; Berger, Minnis, and Sutherland 2017). Related, RegTech can create additional hard information, both by hardening soft information and enabling measurement of previously unrecorded activity. Third, to the extent that RegTech investment complementarities

[24] Our specification here follows research on forecasting COVID cases (Kraemer et al. 2020; Charoenwong, Kwan, and Pursiainen 2020; Friedman et al. 2021).

are scalable, larger BDs may disproportionately gain. For example, larger firms have more customers and therefore more data to construct profitability, risk, and fraud prediction models. As a result, their models will be more accurate and can incorporate more nuances than those of smaller rivals with less data. Similarly, in virtue of their scale and scope, larger firms will have more investment, cross-selling, and synergistic opportunities.[25]

Increasing compliance costs can lead to industry consolidation. For example, a post-Dodd-Frank survey of small banks reports that 26% are contemplating mergers as a response to the increasing regulatory burden and 95% anticipate industry consolidation (Peirce, Robinson, and Stratmann 2014). To study consolidation systematically in our setting, we use an event time version of Equation (1) to model the propensity for BDs to engage in acquisitions. We consider acquisitions of both other BDs and registered investment advisers (IAs), to ensure a sufficient sample of transactions to study. As in other markets, acquisitions are major events, and examining the broadest possible set of transactions is amenable to our BD-year level empirical framework. IAs are natural acquisition targets for BDs: most individual IA employees are dually-registered as BDs (Egan et al. 2019), and IAs and BDs often perform similar services (albeit with different compensation structures and standards of care for customers). IAs can therefore benefit from the back-office infrastructure carrying BDs can offer.

We identify mergers as instances where a given BD or IA disappears from the public registration data, and in the subsequent year 90% or more of its employees join the same BD. Based on our search of media coverage of acquisitions and discussions with a merger advisor in

[25] Routledge (2018) discusses Amazon's acquisition of Whole Foods as an example: "The data Amazon extracts from Whole Foods has more value the larger is Amazon … Big data (and related processing) has larger impacts on large companies" (p. 90).

the BD market, this approach is well suited to measuring consolidation. We classify BDs according to their pre-amendment size and technological sophistication.[26]

The first plot in Figure 1.3 shows an acquisition spike in 2014 for larger BDs with superior technology prior to the amendment. Economically, the increase translates into a doubling in the annual acquisition probability. By contrast, the second plot shows a mild decrease for large BDs with inferior technology prior to the amendment. Similarly, the third plot finds no acquisition increase for small BDs. Together, the evidence points to the amendment hindering smaller, less technologically sophisticated BDs, and providing new opportunities for larger ones to expand the size and scope of their operations.

Beyond consolidation, market structure is also affected by hiring. Then, because the amendment compels technological investment at carrying BDs, it can lead to more advisers leaving noncarrying BDs for (typically larger) carrying BDs.[27] Given the importance of advisers to BD size (advisers are the primary employee type, and employee-client relationships drive assets under management), such turnover has direct implications for market structure.

We use the following OLS specification to study employee flows:

$$y_{i,j,t} = \alpha_{i,j} + \alpha_t + \beta \times PairType_{i,j} \times Post_t + \varepsilon_{i,j,t}, \quad (2)$$

where i indexes origin BDs (where the employee leaves), j indexes destination BDs (where the employee joins), and t indexes years. Thus the unit of observation is BD firm pair-year. The dependent variable is 100 times an indicator for whether an employee left BD_i for BD_j during the

[26] For size, we split the sample at the median headcount, rather than at the 90th percentile of headcount as in Table 3, to ensure a sufficient number of observations in each group. For technological sophistication, we split the sample at the median *Tech Index* as in Table 3.

[27] To illustrate, a recent industry report explains: "Greater scale enables firms to increase these relatively fixed investments and returns on those investments can increase significantly when they support a larger number of advisors and assets under management … in one of (our) most recent surveys, *technology was tied for the top spot among the factors most frequently cited by advisors as influencing their decision to join a BD*" (Martin 2021; emphasis added).

year. $PairType$ refers to indicator variables for each combination of origin and destination BD type (leaves noncarrying, joins carrying; leaves carrying, joins noncarrying; and leaves carrying, joins carrying; the holdout pair is leaves noncarrying, joins noncarrying). $Post$ is an indicator variable equal to one beginning in 2014. $\alpha_{i,j}$ are BD firm pair fixed effects, and α_t are year fixed effects. We cluster standard errors by BD_i and BD_j. Our sample contains only those BDs *i* and *j* where at least one employee leaves or joins during the sample period. Intuitively, our specification compares switching from one BD type to another across the pre- and post-amendment periods, while holding both BD firm-pair-level and year-level heterogeneity constant.

Table 7 shows that after the amendment, the likelihood of an employee switching from a noncarrying to a carrying BD increases. The 0.038 coefficient on *Leaves Noncarrying, Joins Carrying x Post* represents 23% of the unconditional mean switch rate. Column 2 adds interaction terms for other combinations of origin and destination BD type. The coefficient on *Leaves Noncarrying, Joins Carrying x Post* remains significant. By contrast, we find no change in other switch types in the post-amendment period. Finally, column 3 adds origin BD x year fixed effects, to control for economic shocks at the BD that employees depart. Again, our results remain.

The fourth plot in Figure 1.3 presents an event time version of column 1. We find little movement in the pre-amendment period, indicating pre-trends are not responsible for our Table 7 findings. Then switching ramps up in 2014 and 2015, before leveling off (i.e., the amendment appears to have induced a one-time shift from noncarrying to carrying BDs).

Finally, to combine the effects of consolidation and labor flow, we study market concentration at the county-year level. Following Gelman et al. (2021), we measure each BD's market share as the ratio of the total headcount across their branches in the county to total headcount across all branches from all BDs in the county. To ensure sufficient power for our tests, we study only counties with at least 25 employees in the pre-amendment period. To focus on the effects of the amendment, we include only those working at carrying BDs in this calculation. We categorize counties according to their exposure to the amendment, by measuring the proportion of employees in the county working at carrying BDs. High exposure counties are above the median for this proportion (with roughly 17% or more employees at carrying BDs in 2014).

Table 8 finds nontrivial concentration increases among carrying BDs in high exposure counties. The column 1 *High Exposure* x *Post* coefficient of 292.5 represents just over one-third of the within-county standard deviation in HHI. Columns 2 and 3 repeat the test using different exposure thresholds (based on the top quartile or decile of carrying BD employment share, respectively). Our results are similar.

Panel B then repeats these tests, but based on market shares for noncarrying BDs (i.e., those unaffected by the amendment). We find no statistical or economic evidence of concentration changes, indicating that our Panel A findings are driven by the amendment rather than common market structure trends in the financial sector. Likewise, the fifth and sixth plots in Figure 1.3 show a post-amendment concentration increase for carrying BDs but not noncarrying BDs. Last, Panel C of Table 8 examines the number of carrying BDs, and finds a significant decline, in line with both our acquisition and concentration evidence.

6. Conclusion

Using amendments to internal control requirements at U.S. BDs, we show RegTech investments have broad consequences for the financial sector that extend beyond compliance. We first establish that these requirements directly affect technology adoption by compelling both investments in ERP and hiring of technological experts to improve controls and record-keeping. IT budgets rise and profitability declines, particularly for smaller BDs.

Then, we show an indirect effect on technology adoption, stemming from these investments rendering sunk the information quality expenditures that facilitate adoption of complementary software and CRM tools. As a result of this technological investment, carrying BDs subject to the amendment experience significant declines in customer complaints and employee misconduct. However, the estimated savings associated with avoided complaints and misconduct are much less than the IT budget increases. These effects have important consequences for market structure: acquisition activity and market concentration among BDs affected by the amendment increase. Overall, our results shed new light on the consequences of technology-driven compliance, and add to the growing body of work studying technology adoption at FIs from different perspectives (D'Acunto et al. 2019; Fuster et al. 2019; Crouzet et al. 2023; Liberti et al. 2022; Pierri and Timmer 2022).

Though the BD setting has unique features, the nature of the regulation (internal control attestation) and response (technological investment) that we examine are common to other FIs, and are attracting growing attention following the collapse of FTX. Our results point to two potential implications of the growth in RegTech investments in the financial sector. First, technological advances will strengthen the linkages between compliance and operating functions, especially as FIs increasingly rely upon RegTech solutions for compliance and more customer information is digitized. As our results illustrate, such linkages can have important effects on FI service quality and employee misconduct. Second, when combined with large fixed compliance costs, complementarities of the type we document could increase the optimal size of FIs and lead to greater market concentration. Although we cannot speak to the welfare effects of technology-based compliance and concentration, our study motivates additional research on RegTech investments and market structure.

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Figure 1.1: RegTech Investments, Labor Demand, and Profitability

The figures below plot coefficients from an event-time version of our regressions in Tables 2 and 3. *Adopts ERP (%)* is 100 times an indicator variable for whether the BD first adopts an ERP system. *Servers* is the number of servers. *RegTech Jobs* and *Tech-based RegTech Jobs* are the share of each job type as labeled. *IT Budget* is the log of the IT budget. *Profitability* is the ratio of net income to average pre-amendment capital multiplied by 100. The plots for *Adopts ERP (%), IT Budget, and Profitability* (*Servers*, *RegTech Jobs* and *Tech-based RegTech Jobs*) are based on OLS (Poisson, fractional regression) estimation. IT budget figures are winsorized at the 5% level. The holdout year is 2010. Observations are at the BD-year level. All estimations include controls from equation (1) and BD and FINRA district-by-year fixed effects. All plots include one standard error bars, where the standard errors are clustered by BD.

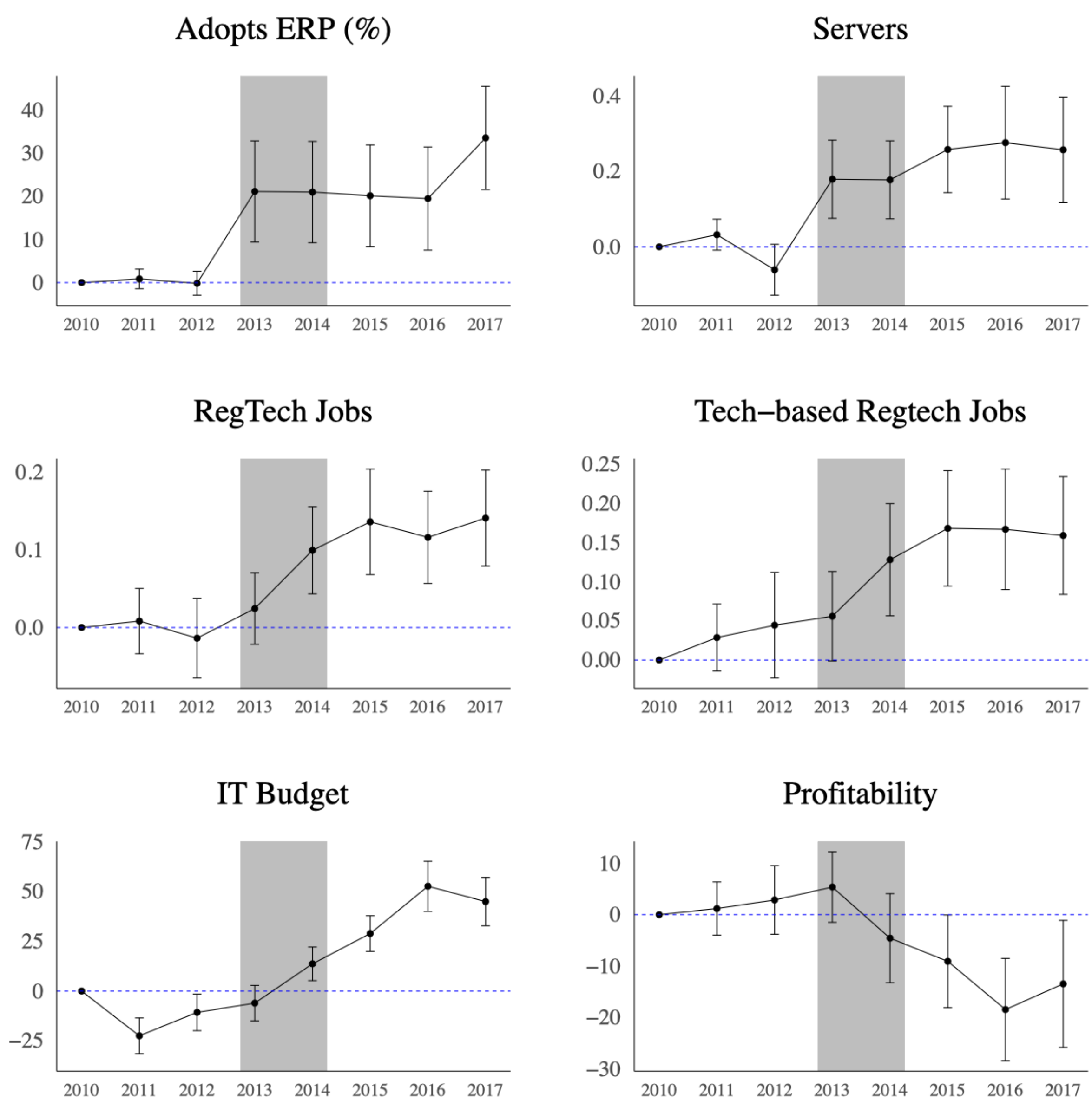


Figure 1.2: Complementary Investments, Customer Complaints, and Employee Misconduct

The figures below plot coefficients from an event-time version of our regressions in Tables 4 and 5. *Comm. Management* is 100 times an indicator variable for having communications management software. *Website CRM* is 100 times an indicator variable for adding a new CRM website technology. *Complaint* is 100 times an indicator variable for whether the BD has a customer complaint recorded on BrokerCheck. *Customer-Reported Misconduct* is 100 times an indicator variable for whether the BD has a customer-reported misconduct incident. All plots are based on OLS estimation. The holdout year is 2010. Observations are at the BD-year level. All estimations include controls from equation (1) and BD and FINRA district-by-year fixed effects. All plots include one standard error bars, where the standard errors are clustered by BD.

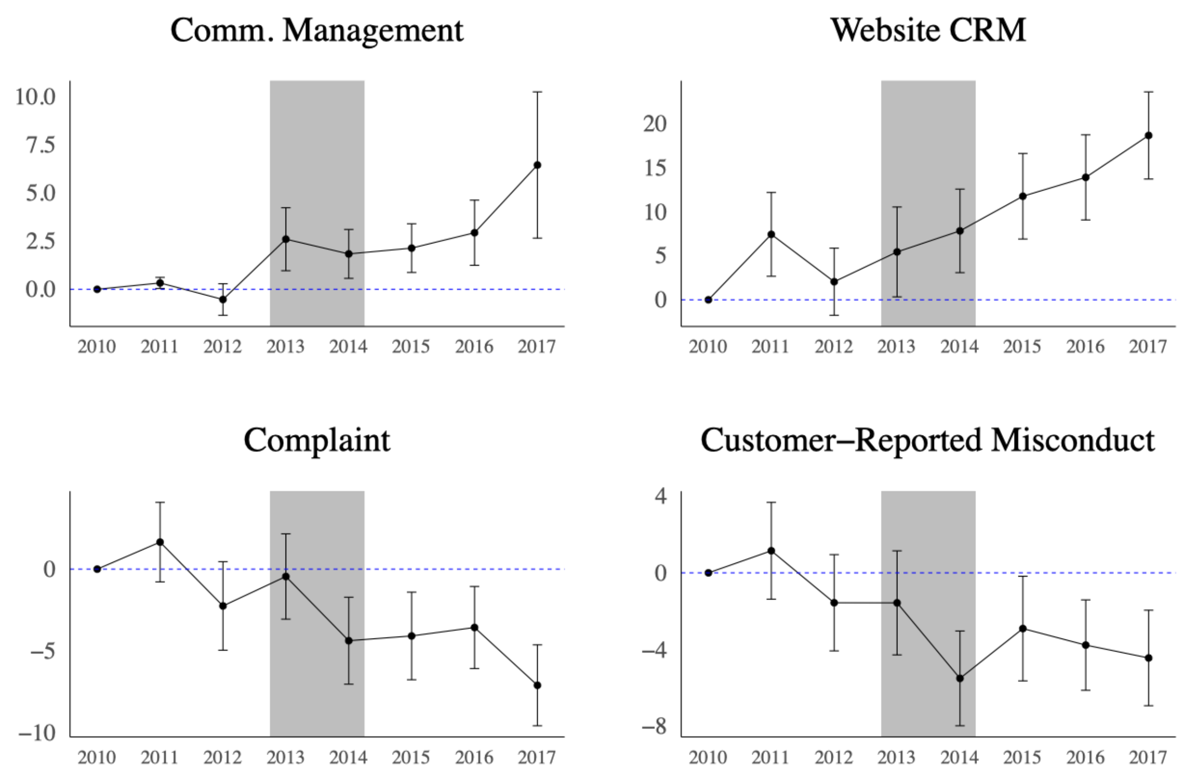


Figure 1.3: Consolidation, Employee Switching, and Market Concentration

The figures below plot coefficients from an event-time version of our acquisition analysis in Section 5 and the regressions in Table 7 column 1 and Table 8. *Acquisition* is 100 times an indicator variable for whether the BD conducts an acquisition. A large (small) BD is one with more (less) than the median headcount in the pre-amendment period, and a high (low) IT BD is one with above (below) median values of *Tech Index* in the pre-amendment period. *Has Switcher* is 100 times an indicator variable for whether the BD has an employee join from another specific BD that year, e.g., BD_i from BD_j. HHI is the Herfindahl-Hirschman index for the county, where the index is based on headcount and spans [0,10000]. The holdout year is 2010. All plots are based on OLS estimation and include the controls and fixed effects from the corresponding regression. Observations for the acquisition (switching, HHI) analyses are at the BD-year (BD-pair-year, county-year) level. All plots include one standard error bars, where the standard errors are clustered as in the corresponding regression table.

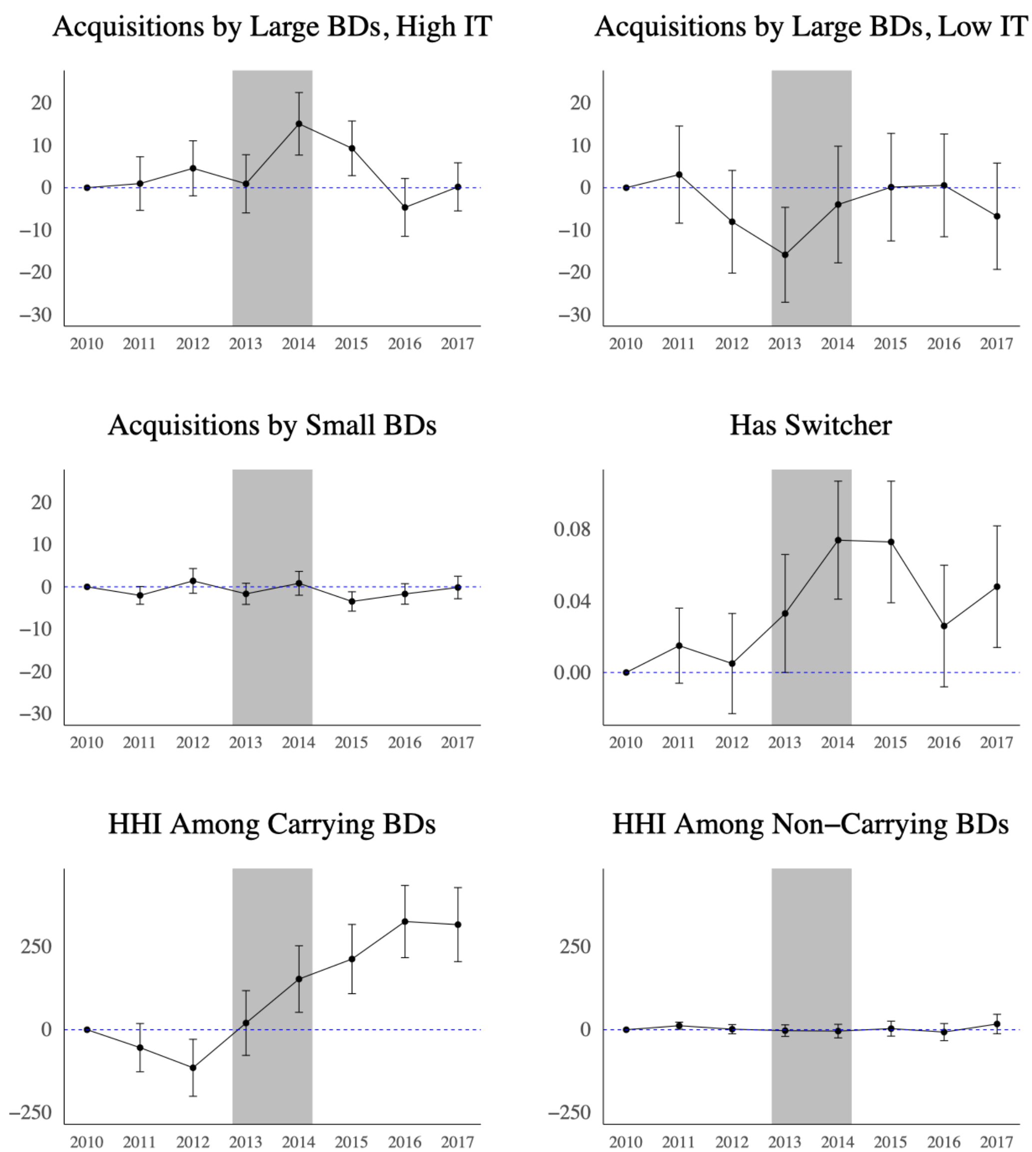


Table 1: Summary Statistics

This table presents summary statistics for BD characteristics in Panel A and RegTech investment variables in Panel B. All observations are at the BD-year level. The BD characteristics sample has 26,721 BD-year observations from 4,660 unique BDs. The profitability sample has 19,845 BD-year observations from 3,990 unique BDs. The Aberdeen Software sample has 7,694 BD-year observations from 2,524 unique BDs. The Aberdeen Hardware sample has 18,313 BD-year observations from 3,227 unique BDs. The Revelio sample has 13,805 BD-year observations from 2,215 unique BDs. Subsequent tables provide the mean and standard deviation of dependent variables for the particular regression sample.

Panel A: BD Characteristics					
Variable	Mean	SD	P25	Median	P75
BD Characteristics:					
Total Assets ($000s)	1,261,841	16,879,300	143	668	4,883
Total Net Capital ($000s)	647,952	87,408,383	61	293	1,905
Treated	0.054	0.227	0	0	0
Post	0.474	0.499	0	0	1
Lag Num. Employees	211	1,709	5	11	37
Lag Avg. Tenure (years)	6.219	5.311	2.600	4.800	8.027
Lag Fraction of Dual-Registered Employees	0.294	0.309	0.000	0.200	0.523
Fraction of Employees with Complaint History	0.045	0.101	0.000	0.000	0.041
Complaint Measures:					
1(Complaints > 0)	0.099	0.299	0	0	0
1(Customer-reported Misconduct> 0)	0.075	0.264	0	0	0
Financial Measures:					
Profitability	41.396	217.685	-13.557	5.454	38.39
Panel B: RegTech Investments					
Aberdeen Software:					
Adopts ERP (%)	12.689	33.292	0	0	0
Adds Additional ERP (%)	87.900	32.623	100	100	100
Aberdeen Hardware:					
Servers	470	2,723	2	6	45
IT Budget ($000s)	49,921	311,872	110	447	3,990
Revelio:					
RegTech Jobs	0.098	0.130	0.000	0.062	0.136
Tech-based RegTech Jobs	0.051	0.096	0.000	0.012	0.061
Compliance Jobs	0.047	0.084	0.000	0.025	0.062

Table 2: RegTech Investments and Labor Demand

This table studies RegTech investments and labor demand using Equation (1). In column 1 (2), *Adopts ERP % (Adds Additional ERP %)* is 100 times an indicator variable for adopting ERP for the first time (adding an additional ERP program). In columns 3-6, the dependent variable is the number of servers or the share of each job type as labeled. *Post* is an indicator variable equal to one starting in 2014. *Treated* is an indicator variable equal to one for carrying BDs (static throughout the sample). Columns 1-2 (3, 4-6) use OLS (Poisson, fractional regression) estimation. The sample in column 1 (2) is limited to BDs without (with) ERP in the pre-amendment period. Observations are at the BD-year level. All regressions include controls from Equation (1) and BD and FINRA district-by-year fixed effects. Standard errors are clustered by BD and shown in parentheses. * signifies $p < 0.1$, ** signifies $p < 0.05$, and *** signifies $p < 0.01$. At the bottom of the table, we report the share of sample BDs that are affected by the amendment ("Treated Share"), as well as the mean and standard deviation of the transformed dependent variable.

Dep Var:	Adopts ERP (%)	Adds Additional ERP (%)	Servers	RegTech Jobs	Tech-based RegTech Jobs	Compliance Jobs
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	16.332**	1.854	0.189**	0.118***	0.122**	0.074
	(7.583)	(1.429)	(0.081)	(0.039)	(0.048)	(0.055)
N	2,921	3,443	16,378	13,766	13,766	13,766
R^2	0.845	0.885	0.883	0.207	0.271	0.200
Treated Share	0.072	0.184	0.074	0.071	0.071	0.071
Mean of Dep Var	10.476	84.577	364.173	0.098	0.051	0.047
SD of Dep Var	30.629	36.122	1,693.583	0.130	0.096	0.084
Sample	No ERP in pre-period	Has ERP in pre-period	Full	Full	Full	Full

Table 3: Profitability

This table studies profitability using Equation (1). In columns 1, 3 and 4, the dependent variable is *IT Budget*, 100 times the log of the IT budget. In columns 2 and 5-8 the dependent variable is *Profitability*, the ratio of net income to average pre-amendment capital multiplied by 100. *Post* is an indicator variable equal to one starting in 2014. *Treated* is an indicator variable equal to one for carrying BDs. The sample in columns 3 and 5 (4 and 6) is limited to large (small) BDs. We define a large (small) BD as one with more (less) than the 90th percentile of headcount in the pre-amendment period. The sample in column 7 (8) is limited to BDs with above (below) median values of *Tech Index* in the pre-amendment period. *Tech Index* is the average Z-score for the BD's investments in ERP software, servers, and CRM website technologies. Observations are at the BD-year level. All regressions include controls from Equation (1) and BD and FINRA district-by-year fixed effects. Standard errors are clustered by BD and shown in parentheses. * signifies $p < 0.1$, ** signifies $p < 0.05$, and *** signifies $p < 0.01$. At the bottom of the table, we report the share of sample BDs that are affected by the amendment, as well as the mean and standard deviation of the transformed dependent variable.

Dep Var:	IT Budget	Profitability	IT Budget	IT Budget	Profitability	Profitability	Profitability	Profitability
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated × Post	23.843***	-13.659**	4.286	28.737***	0.246	-20.828*	-13.392*	-28.851***
	(6.168)	(6.586)	(8.086)	(9.949)	(4.368)	(11.551)	(7.532)	(11.007)
N	13,214	19,793	2,259	10,676	2,356	17,437	5,804	5,810
R^2	0.938	0.624	0.942	0.917	0.763	0.620	0.687	0.655
Treated Share	0.074	0.055	0.231	0.043	0.229	0.031	0.129	0.031
Mean of Dep Var	1,361.518	40.327	1,621.668	1,307.702	13.653	43.584	26.865	49.197
SD of Dep Var	250.942	209.742	228.453	218.540	54.256	221.343	158.237	209.785
Sample	Full	Full	Large	Small	Large	Small	High IT	Low IT

Table 4: Complementary Investments

This table studies complementary investments using Equation (1). The dependent variables in columns 1 and 4 are 100 times indicator variables for having the software type labeled in the column header. The dependent variables in columns 2 and 3 are 100 times indicators for adding a new website technology of the type labeled in the column header. *Post* is an indicator variable equal to one starting in 2014, and *Treated* is an indicator variable equal to one for carrying BDs. Observations are at the BD-year level. All regressions include controls from Equation (1) and BD and FINRA district-by-year fixed effects. Standard errors are clustered by BD and shown in parentheses. * signifies $p < 0.1$, ** signifies $p < 0.05$, and *** signifies $p < 0.01$. At the bottom of the table, we report the share of sample BDs that are affected by the amendment, as well as the mean and standard deviation of the transformed dependent variable.

Dep Var:	Comm. Management	Website CRM	Website Premium	Job App. And Payroll
	(1)	(2)	(3)	(4)
Treated × Post	3.005**	10.507***	10.573***	0.469
	(1.416)	(2.872)	(2.876)	(1.720)
N	6,262	10,654	10,654	6,262
R^2	0.965	0.290	0.314	0.832
Treated Share	0.133	0.094	0.094	0.133
Mean of Dep Var	25.515	18.315	20.412	24.501
SD of Dep Var	43.598	38.681	40.307	43.013

Table 5: Technological Investment, Customer Complaints, and Misconduct

This table studies customer complaints and misconduct using Equation (1). The dependent variable in Panel A, column 1 is 100 times an indicator variable for whether the BD has a customer complaint recorded on BrokerCheck that year. The dependent variable in column 2 is 100 times an indicator variable for whether the BD has a customer-reported misconduct incident that year. The dependent variable in column 3 is 100 times an indicator variable for whether the BD has a complaint with alleged damages of at least $5,000. In Panel B, *Tech Index* is the average Z-score for the BD's investments in ERP software, servers, and CRM website technologies. *Post* is an indicator variable equal to one starting in 2014, and *Treated* is an indicator variable equal to one for carrying BDs. Observations are at the BD-year level. All regressions include controls from Equation (1) and BD and FINRA district-by-year fixed effects. Standard errors are clustered by BD and shown in parentheses. * signifies p < 0.1, ** signifies p < 0.05, and *** signifies p < 0.01. At the bottom of the table, we report the share of sample BDs that are affected by the amendment, as well as the mean and standard deviation of the transformed dependent variable.

Panel A: Reduced-Form			
Dep Var:	Complaint	Customer-reported Misconduct	Complaint >$5000
	(1)	(2)	(3)
Treated × Post	-4.420***	-3.580**	-4.321***
	(1.482)	(1.391)	(1.536)
N	17,810	17,810	17,810
R^2	0.700	0.668	0.695
Treated Share	0.073	0.073	0.073
Mean of Dep Var	12.847	9.888	11.786
SD of Dep Var	33.462	29.981	32.245

Panel B: Instrumental Variables				
Dep Var:	Tech Index	Complaint	Customer-reported Misconduct	Complaint >$5000
	(1)	(2)	(3)	(4)
Treated × Post	0.173***			
	(0.029)			
$\widehat{\text{Tech Index}}$		-25.557***	-20.704**	-24.984**
		(9.496)	(8.474)	(9.823)
F-Statistic	35.7			
N	17,810	17,810	17,810	17,810
R^2	0.866	0.654	0.634	0.649
Treated Share	0.073	0.073	0.073	0.073
Mean of Dep Var	0.000	12.847	9.888	11.786
SD of Dep Var	0.784	33.462	29.981	32.245

Table 6: Investigating Regulator and Auditor Attention

This table studies complaints using Equation (1). The dependent variable is 100 times an indicator variable for whether the BD has a complaint of the type labeled in the column header recorded on BrokerCheck that year. *Post* is an indicator variable equal to one starting in 2014, and *Treated* is an indicator variable equal to one for carrying BDs. *Retail* is an indicator variable for whether the BD offers retail-facing products, including investment advice, mutual funds, variable life insurance, and debt products. In column 3 (5), *Distant* is an indicator variable for whether the BD is farther than the median from its nearest FINRA office (from its auditor's office). *Auditor Tolerant* is an indicator for the BD's auditor having a size-adjusted above-median share of clients with a customer complaint recorded on BrokerCheck between 2010 and 2013. The sample in columns 2 and 3 is limited to Retail BDs. All regressions include controls from Equation (1) and BD and FINRA district-by-year fixed effects. Standard errors are clustered by BD and shown in parentheses. * signifies $p < 0.1$, ** signifies $p < 0.05$, and *** signifies $p < 0.01$. At the bottom of the table, we report the share of sample BDs that are affected by the amendment, as well as the mean and standard deviation of the transformed dependent variable.

Dep Var:	Complaint	Regulator-reported	Regulator-reported	Complaint	Complaint	Auditor-related Complaint	Not Auditor-related Complaint
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treated × Post	-0.895	0.931	-0.468	-4.108**	-5.286***	0.056	-4.710***
	(1.376)	(1.933)	(2.395)	(1.948)	(2.017)	(1.303)	(1.460)
Treated × Post × Retail	-4.986**						
	(2.434)						
Treated × Post × Distant			2.683		2.170		
			(3.710)		(2.868)		
Treated × Post × Auditor Tolerant				-0.323			
				(3.024)			
N	17,810	10,944	10,944	16,035	17,802	17,810	17,810
R^2	0.699	0.492	0.492	0.703	0.699	0.503	0.702
Treated Share	0.073	0.083	0.083	0.077	0.073	0.073	0.073
Mean of Dep Var	12.847	10.124	10.124	13.096	12.847	3.330	12.487
SD of Dep Var	33.462	30.166	30.166	34.737	33.462	17.941	33.058
Sample	Full	Retail	Retail	Full	Full	Full	Full

Table 7: Employee Switching

This table studies employee switching using Equation (2). The dependent variable is 100 times an indicator variable for whether the BD has an employee join from another specific BD that year, e.g., BD_i from BD_j. The independent variables are indicators for combinations of types of origin and destination BDs for the employee, times *Post*, an indicator variable equal to one starting in 2014. The sample includes all pairs of destination and origin BDs involving BDs with at least one employee switch during the sample window. Observations are at the BD firm pair-year level. Columns 1 and 2 include origin-by-destination BD-pair and year fixed effects, and column 3 adds origin-by-year fixed effects. Standard errors are clustered by BD_i and BD_j and shown in parentheses. * signifies p < 0.1, ** signifies p < 0.05, and *** signifies p < 0.01.

Dep Var:	Has Switcher	Has Switcher	Has Switcher
	(1)	(2)	(3)
Leaves Noncarrying, Joins Carrying × Post	0.038**	0.041**	0.041**
	(0.016)	(0.016)	(0.016)
Leaves Carrying, Joins Noncarrying × Post		0.024	
		(0.015)	
Leaves Carrying x Joins Carrying × Post		0.096	
		(0.096)	
N	53,595,473	53,595,473	53,595,473
R^2	0.387	0.387	0.388
Mean Dep Var	0.163	0.163	0.163
SD Dep Var	4.029	4.029	4.029

Table 8: Market Concentration

This table studies market concentration. The dependent variable in Panels A and B is the Herfindahl-Hirschman index for the county-year, where the index is based on headcount and spans [0,10000]. The dependent variable in Panel C is the number of carrying BDs in the county. *High Exposure* an indicator variable equal to one for counties with an above-threshold proportion of pre-amendment employment at carrying BDs. The threshold is labeled in the column header. *Post* is an indicator variable equal to one starting in 2014. Panels A and B (C) use OLS (Poisson) estimation. Observations are at the county-year level. All regressions include county and year fixed effects, and standard errors are clustered by county and shown in parentheses. * signifies p < 0.1, ** signifies p < 0.05, and *** signifies p < 0.01.

Panel A: HHI among Carrying BDs			
Dep Var:		HHI	
High Exposure Share Threshold =	Median	75th Percentile	90th Percentile
	(1)	(2)	(3)
High Exposure × Post	292.527***	240.494***	268.672***
	(65.818)	(61.475)	(87.479)
N	8,800	8,800	8,800
R^2	0.855	0.854	0.854
Mean of Dep Var	3,468.320	3,468.320	3,468.320
SD of Dep Var	2,087.640	2,087.640	2,087.640
Num. Treated Counties	671	228	53

Panel B: HHI among Noncarrying BDs			
Dep Var:		HHI	
High Exposure Share Threshold =	Median	75th Percentile	90th Percentile
	(1)	(2)	(3)
High Exposure × Post	-11.420	20.296	41.841
	(18.047)	(23.507)	(47.201)
N	8,800	8,800	8,800
R^2	0.938	0.938	0.938
Mean of Dep Var	1,244.835	1,244.835	1,244.835
SD of Dep Var	838.210	838.210	838.210

Panel C: Number of Carrying BDs			
Dep Var:		Number of Carrying BDs	
High Exposure Share Threshold =	Median	75th Percentile	90th Percentile
	(1)	(2)	(3)
High Exposure × Post	-0.070***	-0.059***	-0.091***
	(0.008)	(0.010)	(0.021)
N	8,776	8,776	8,776
R^2	0.992	0.992	0.992
Mean of Dep Var	8.230	8.230	8.230
SD of Dep Var	9.103	9.103	9.103

Online Appendix

A.1. Data Merging and Cleaning

We merge our main sample of BDs with Aberdeen CiTDB, BuiltWith, and Revelio using a variety of methods, as the databases have no common identifiers. For these merges, we include observations that have values of zero and drop observations with missing data.

To match BDs to Aberdeen, we first use the website for each BD included in the LaRoche Research database. According to Aberdeen, this is the most appropriate identifier because their first- and third-party databases track firms using their websites. Second, we supplement BDs missing from the LaRoche Research database using an ensemble of methods. Specifically, we extract CIK codes and EINs contained on Form BD, which we use to link to firmographic databases such as Orbis, containing DUNS numbers and websites. The DUNS numbers and websites serve as common identifiers with Aberdeen. We also conduct fuzzy-name matching on name and phone number and name and address directly between Form BD and Aberdeen. Finally, we use the Bing Search API to identify web search results for BDs and manually screen out false positives. The majority of final matches come from the LaRoche Research database. After merging, we eliminate observations missing controls, and clear data errors most likely related to Aberdeen's data modeling and collection process. Specifically, we eliminate observations where the BD has more than 7,500 servers in a majority of years and cap servers to be no more than the number of employees.[28] To ensure sufficient data coverage in Aberdeen and avoid false positives in our technology adoption tests, we limit our sample to BDs with at least five software types by the end of our sample period or five website technologies in a year. The final software sample with nonmissing controls contains 6,262 BD-

[28] This filter affects 1.6% of observations. Other filters, such as capping at 5,000 or 6,000 servers, produce very similar results.

year observations from 2,299 BDs. Our final server sample with nonmissing controls includes 3,209 unique BDs and 16,378 BD-year observations.

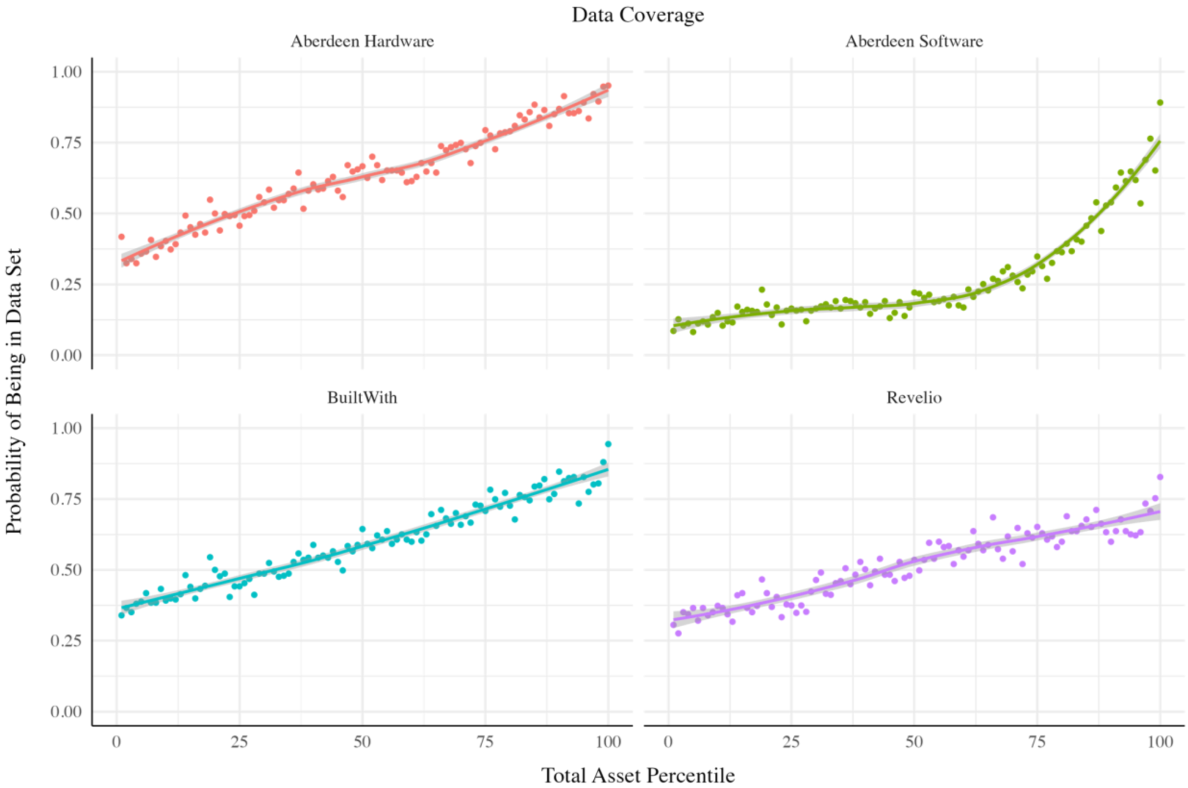
To match BDs to BuiltWith we use the procedure above, supplemented by the Bing Search API. Noncoverage implies that BDs do not have websites (which is the case for some smaller BDs) or that BuiltWith lacks information on their website. To ensure sufficient data coverage in BuiltWith and avoid false positives in our technology adoption tests, we limit our sample to BDs with at least five software types by the end of our sample period or five website technologies in a year. Our final sample with nonmissing control variables includes 1,757 unique BDs and 10,654 BD-year observations.

To match BDs to the Revelio data, we use the website provided by LaRoche Research as well as any exact matches on firm name. This process leverages the same linktable we created in the Aberdeen merge. This yields 14,797 observations. Our final sample with nonmissing controls includes 2,215 unique BDs and 13,766 BD-year observations.

Figure A.1 below plots the proportion of BDs covered by each dataset as a function of BD size. Naturally, coverage is better for larger BDs in all of the datasets.

Figure A.1 Sample Coverage

This figure illustrates the sample coverage for the Aberdeen Hardware, Aberdeen Software, BuiltWith, and Revelio samples.



A.2. Business Model Differences

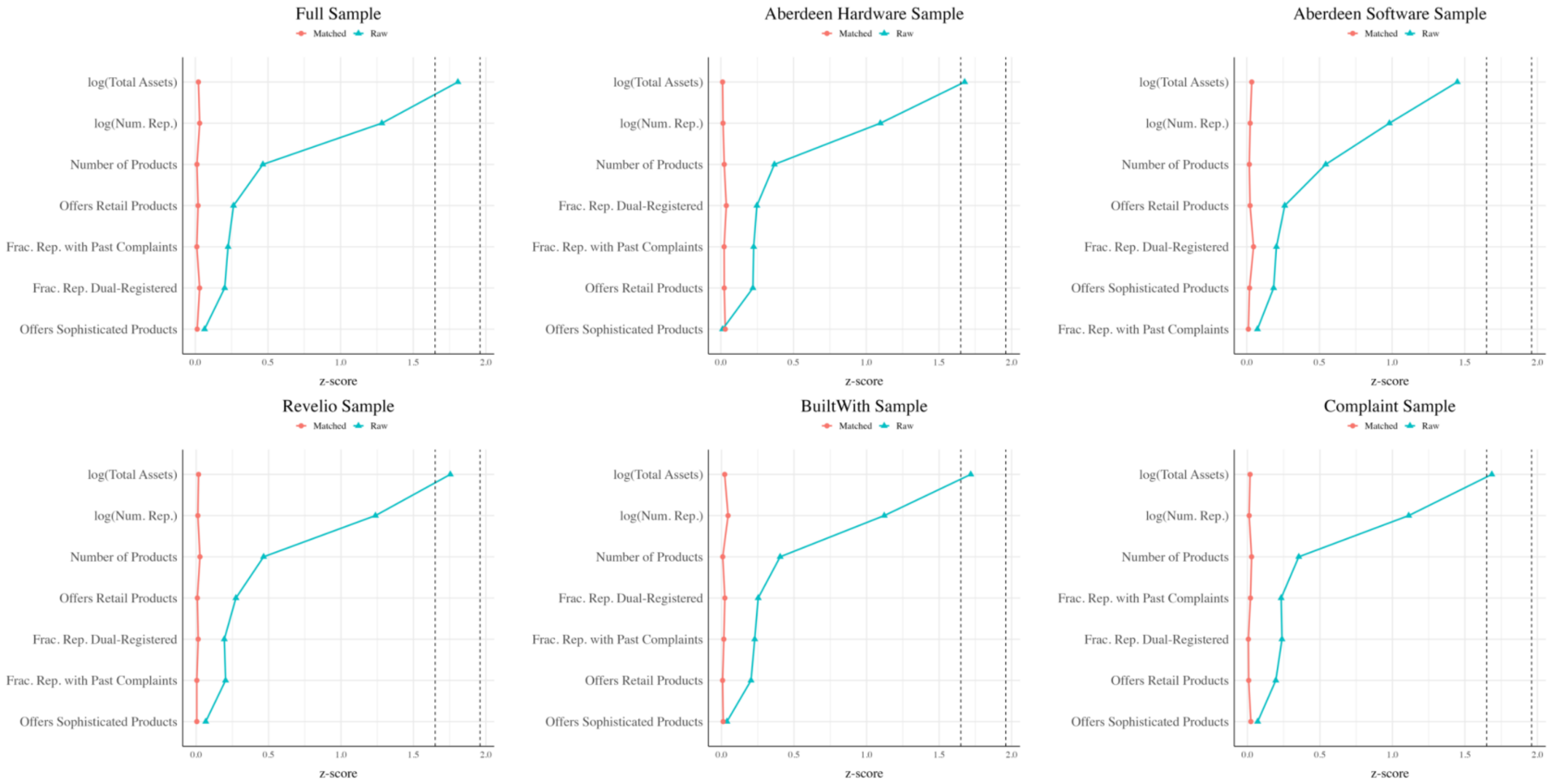
Table A.1: Summary Statistics by BD Type

This table reports summary statistics by BD type.

	Mean	SD	Mean	SD
	Noncarrying BD		Carrying BD	
BD Characteristics:				
Total Assets ($000s)	494,613.6	10,648,261	14,537,410	55,393,419
Total Net Capital ($000s)	64,429	6,694,028	10,769,442	373,321,289
Treated	0.000	0.000	1.000	0.000
Post	0.472	0.499	0.509	0.500
Lag Num. Employees	139	1,044	1,468	5,755
Lag Avg. Tenure (years)	6.271	5.360	5.295	4.176
Lag Fraction of Dual-Registered Employees	0.297	0.311	0.240	0.265
Fraction of Employees with Complaint History	0.046	0.103	0.027	0.055
Complaint Measures:				
1(Complaints > 0)	0.093	0.291	0.206	0.405
1(Customer Reported Misconduct> 0)	0.069	0.254	0.178	0.383
	Mean	SD	Mean	SD
	Noncarrying BD		Carrying BD	
Aberdeen Software:				
Adopts ERP (%)	11.715	32.167	27.737	44.934
Adds Additional ERP (%)	86.604	34.07	93.248	25.133
Aberdeen Hardware:				
Servers	354	2,143	1,860	6,262
IT Budget ($000s)	37,842	259,019	194,722	660,718
Revelio:				
RegTech Jobs	0.096	0.130	0.138	0.114
Tech-based RegTech Jobs	0.049	0.095	0.088	0.103
Compliance Jobs	0.047	0.087	0.050	0.037
Financial Measures:				
Profitability	44.153	224.712	-1.720	111.462

Figure A.2. Covariate Balance

This figure illustrates the covariate balance for the matched and unmatched samples, based on the absolute Z-score of the difference between carrying and noncarrying BDs for each variable. Variables are first demeaned within subclass, such that we include fixed effects within subclass. Z-scores use standard deviations pooled across carrying and noncarrying BDs. The two dashed lines represent 90% and 95% significance.



A.3. Additional Robustness Tests

Table A.2: No Controls

This table repeats our key results without including control variables in the regression. All regressions include BD and FINRA district-by-year fixed effects. Standard errors are clustered by BD and shown in parentheses. * signifies $p < 0.1$, ** signifies $p < 0.05$, and *** signifies $p < 0.01$.

Panel A: Technology Adoption (Table 2)

Dep Var:	Adopts ERP (%)	Adds Additional ERP (%)	Servers	RegTech Jobs	Tech-based RegTech Jobs	Compliance Jobs
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	17.531**	1.719	0.178**	0.120***	0.128***	0.069
	(7.834)	(1.417)	(0.082)	(0.038)	(0.047)	(0.054)
N	2,921	3,443	16,378	13,766	13,766	13,766
R^2	0.843	0.884	0.879	0.207	0.271	0.200
Treated Share	0.072	0.184	0.074	0.071	0.071	0.071
Mean of Dep Var	10.476	84.577	364.173	0.098	0.051	0.047
SD of Dep Var	30.629	36.122	1,693.583	0.130	0.096	0.084
Sample	No ERP in pre-Period	Has ERP in pre-period	Full	Full	Full	Full

Panel B: Profitability (Table 3)

Dep Var:	IT Budget	Profitability	IT Budget	IT Budget	Profitability	Profitability
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	25.644***	-14.872**	3.758	31.948***	0.943	-22.324**
	(6.258)	(6.451)	(8.268)	(10.149)	(4.509)	(11.191)
N	13,214	19,793	2,259	10,676	2,356	17,437
R^2	0.938	0.623	0.941	0.917	0.761	0.619
Sample	Full	Full	Large	Small	Large	Small
Treated Share	0.074	0.055	0.231	0.043	0.229	0.031
Mean of Dep Var	1,361.518	40.327	1,621.668	1,307.702	13.653	43.584
SD of Dep Var	250.942	209.742	228.453	218.540	54.256	221.343
Sample	Full	Full	Large	Small	Large	Small

Panel C: Complementarity (Table 4, Panel B)

Dep Var:	Comm. Management	Website CRM	Website Premium	Job App. and Payroll
	(1)	(2)	(3)	(4)
Treated × Post	3.085**	10.712***	11.189***	0.427
	(1.448)	(2.891)	(2.874)	(1.730)
N	6,262	10,654	10,654	6,262
R^2	0.965	0.289	0.314	0.832
Treated Share	0.133	0.094	0.094	0.133
Mean of Dep Var	25.535	18.406	20.481	24.465
SD of Dep Var	43.609	38.755	40.358	42.991

Panel D: Complaints (Table 5)

Panel D.1: Reduced-Form Analyses

Dep Var:	Complaint	Customer-Reported Misconduct	Complaint >$5000
	(1)	(2)	(3)
Treated × Post	-3.981**	-2.961**	-3.934**
	(1.554)	(1.425)	(1.591)
N	17,810	17,810	17,810
R^2	0.696	0.667	0.692
Treated Share	0.073	0.073	0.073
Mean of Dep Var	12.847	9.966	11.786
SD of Dep Var	33.462	29.956	32.245

Panel D.2: Instrumental Variables Analyses

Dep Var:	Tech Index	Complaint	Customer-Reported Misconduct	Complaint >$5000
	(1)	(2)	(3)	(4)
Treated × Post	0.181***			
	(0.029)			
$\widehat{\text{Tech Index}}$		-22.031**	-17.172**	-21.768**
		(9.312)	(8.386)	(9.556)
F-Stat	39.57			
N	17,810	17,810	17,810	17,810
R^2	0.865	0.661	0.641	0.657
Treated Share	0.073	0.073	0.073	0.073
Mean of Dep Var	0.000	12.813	9.862	11.754
SD of Dep Var	0.784	33.424	29.816	32.208

Table A.3: ERP Adoption Robustness

This table evaluates the robustness of our Table 2, column 1 results. The dependent variable, *Adopts ERP (%)*, is 100 times an indicator variable for adopting ERP for the first time. Columns 1 and 2 perform a matching analysis. Column 2 eliminates observations without sufficient balance between treated and control BDs. In column 3, *Size* is an indicator variable for BDs with above-median lag headcount. Column 4 eliminates bank-affiliated BDs. Column 5 eliminates observations from before 2012. Column 6 includes separate year fixed effects for BDs where the majority of employees are dually registered. Column 7 eliminates BDs with mergers during our sample window. In column 8, the control group comprises U.S. banks rather than noncarrying BDs. *Post* is an indicator variable equal to one starting in 2014, and *Treated* is an indicator variable equal to one for carrying BDs. The sample is limited to BDs without ERP in the pre-amendment period. Observations are at the BD-year level. All regressions in columns 1-7 include controls from Equation (1) and BD and FINRA district-by-year fixed effects. Standard errors are clustered by BD and shown in parentheses. * signifies p < 0.1, ** signifies p < 0.05, and *** signifies p < 0.01.

Dep Var:	Adopts ERP (%)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated × Post	16.485**	14.055*	16.385**	16.718**	11.197**	16.179**	16.191**	20.342**
	(7.152)	(8.463)	(7.650)	(8.490)	(4.976)	(7.664)	(7.669)	(7.546)
Size × Post			-0.2286					
			(4.708)					
Specification	Matching Analysis	Matching Analysis – Drop Subclasses with Imbalance	Size Trends	Drop Bank Affiliates	Keep Only ≥ 2012	IA x Year FEs	Drop Mergers	Banks as Control
N	2,921	1,247	2,926	2,576	2,586	2,926	2,882	3,506
R^2	0.866	0.848	0.847	0.851	0.894	0.846	0.845	0.933
Treated Share	0.072	0.157	0.072	0.065	0.067	0.072	0.073	1.000
Mean Dep Var	10.476	13.793	10.476	10.463	11.856	10.476	10.532	18.000
SD Dep Var	30.629	34.497	30.629	30.613	32.333	30.629	30.702	38.496

Table A.4: Profitability based on Return on Assets

This table studies profitability using Equation (1). The dependent variable is *Profitability*, the ratio of net income to average pre-amendment assets (ROA) multiplied by 100. *Post* is an indicator variable equal to one starting in 2014. *Treated* is an indicator variable equal to one for carrying BDs. The sample in column 2 (3) is limited to large (small) BDs. We define a large (small) BD as one with more (less) than the 90th percentile of headcount in the pre-amendment period. The sample in column 4 (5) is limited to BDs with above (below) median values of *Tech Index* in the pre-amendment period. *Tech Index* is the average Z-score for the BD's investments in ERP software, servers, and CRM website technologies. Observations are at the BD-year level. All regressions include controls from Equation (1) and BD and FINRA district-by-year fixed effects. Standard errors are clustered by BD and shown in parentheses. * signifies $p < 0.1$, ** signifies $p < 0.05$, and *** signifies $p < 0.01$.

Dep Var:	ROA	ROA	ROA	ROA	ROA
	(1)	(2)	(3)	(4)	(5)
Treated × Post	-11.450***	1.360	-18.246***	-10.135**	-22.146**
	(3.918)	(2.311)	(6.418)	(4.909)	(8.720)
N	20,063	2,356	17,460	5,812	5,818
R^2	0.637	0.815	0.632	0.685	0.665
Treated Share	0.054	0.229	0.031	0.129	0.031
Mean of Dep Var	32.698	8.024	35.779	19.275	37.862
SD of Dep Var	170.859	30.159	179.718	115.732	169.746
Sample	Full	Large	Small	High IT	Low IT

Table A.5: Complaint Analysis Robustness

This table assesses the robustness of our Table 5 results using Equation (1). The dependent variable is 100 times an indicator variable for whether the BD has a customer complaint recorded on BrokerCheck that year. Columns 1 and 2 perform a matching analysis. Column 2 eliminates observations without sufficient balance between treated and control BDs. In column 3, *Size* is an indicator variable for BDs with above-median lag headcount. Column 4 eliminates bank-affiliated BDs. In column 5, *Distant* is an indicator variable for whether the BD is further than the median from its nearest FINRA office. *Post* is an indicator variable equal to one starting in 2014, and *Treated* is an indicator variable equal to one for carrying BDs. Observations are at the BD-year level. All regressions include controls from equation (1) and BD and FINRA district-by-year fixed effects. Standard errors are clustered by BD and shown in parentheses. * signifies $p < 0.1$, ** signifies $p < 0.05$, and *** signifies $p < 0.01$.

Dep Var:	Complaint	Complaint	Complaint	Complaint	Complaint
	(1)	(2)	(3)	(4)	(5)
Treated × Post	-4.558***	-4.079**	-3.940***	-4.803***	-5.943**
	(1.526)	(1.775)	(1.499)	(1.587)	(2.448)
Post × Size			-2.281***		
			(0.622)		
Post × Distant					0.958
					(0.897)
Treated × Post × Distant					2.774
					(3.023)
Specification	Matching Analysis	Matching – Drop sub-classes w/ High Imbalance	Size Trends	Drop Bank Affiliates	Distance to Regulator
N	17,810	6,523	17,810	15,984	17,810
R^2	0.701	0.798	0.699	0.695	0.699
Treated Share	0.073	0.177	0.073	0.068	0.073
Mean Dep Var	12.847	20.957	12.847	12.800	12.847
SD Dep Var	33.462	33.462	33.462	33.462	33.462

Table A.6: Technological Investment and Customer Complaints during COVID-19

This table studies customer complaints using the following equation:

$$y_{i,t} = \alpha_i + \alpha_{f(i,t),t} + \beta \times Tech\ Index_{i,2017} \times COVID_t + \Gamma' \times X_{i,t-1} + \varepsilon_{i,t}$$

where i indexes BDs, t indexes quarters, and $f(i,t)$ is the FINRA district for BD i during quarter t. The dependent variable is 100 times an indicator variable for whether the BD has a registered customer complaint that quarter. $COVID$ is an indicator variable equal to one starting in Q2 2020. *Tech Index*$_{2017}$, defined earlier, is measured in 2017 to capture the BD's technological capabilities before the event window. *Log Cases* is the natural logarithm of the number of COVID cases in a county-quarter. α_i are BD fixed effects and $\alpha_{f(i,t),t}$ are FINRA district-by-year fixed effects. We include cubic controls for the lag number of employees. The sample period runs from Q3 2018 to Q3 2021 and omits Q1 2020 (during which the World Health Organization declared a global pandemic). We cluster standard errors by BD. * signifies p < 0.1, ** signifies p < 0.05, and *** signifies p < 0.01.

Dep Var:	Complaint	
	(1)	(2)
COVID × Tech Index$_{2017}$	-0.727**	
	(0.314)	
Log Cases × Tech Index$_{2017}$		-0.118***
		(0.034)
Log Cases		0.161**
		(0.063)
N	20,680	20,680
R^2	0.610	0.610
Mean Dep Var	6.720	6.720
SD Dep Var	25.037	25.037