Can Blockchain Technology Help Overcome Contractual Incompleteness? Evidence from State Laws[*]

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Abstract: Real-world contractual agreements between firms are often incomplete, leading to suboptimal investment and loss of value in supply-chain relationships. To what extent can blockchain technology help alleviate problems arising from contractual incompleteness? We examine this issue by exploiting a quasi-natural experiment based on the staggered adoption of U.S. state laws that increased firms' in-state ability to develop, adopt, and use blockchain technology. We find that, after exposure to a pro-blockchain law, firms with greater asset specificity exhibit more positive changes to Tobin's Q, R&D, and blockchain-related innovation. Also, such firms appear to rely less on vertical integration, form more strategic alliances, and shift their emphasis to less geographically proximate customers. Overall, our results suggest that blockchain technology can help firms remedy constraints and inefficiencies arising from contractual incompleteness.

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1. Introduction

Contractual agreements between suppliers and customers are very often incomplete due to real-world transaction costs and limited verifiability of contingencies. This contractual incompleteness can lead to suboptimal investment and a consequent loss of value in supplier-customer relationships (Williamson, 1975; Klein, Crawford, and Alchian, 1978; Klein, 1996). A large literature studies the role of organizational form, property rights, and long-term agreements in mitigating the underinvestment problem (Grossman and Hart, 1986; Joskow, 1987; Hart and Moore, 1990). Yet, there has been little exploration of how new digital technologies can improve the contracting process. In this paper, we aim to fill this gap by empirically examining the effects of blockchain, a prominent and newly emerging digital technology, on firms and their ability to contract efficiently with customers.

Blockchains are distributed ledgers that can record information in a transparent, tamper-proof way and automatically execute or control certain actions when predetermined conditions are met. Because blockchain technology enables parties to implement, via decentralized consensus, the automated collection, recordation, and distribution of information (Nakamoto, 2008; Abadi and Brunnermeier, 2018; Cong and He, 2019; Catalini and Gans, 2020; Chod et al., 2020), many real-world blockchain applications have emerged across different industries. For instance, blockchains are becoming integral to product tracking systems, which are projected to add $962 billion to the global annual GDP by 2030.[1] Blockchain technology is also becoming increasingly widespread in important industrial sectors such as manufacturing, healthcare, and financial services (Chang and Chen, 2020; Dutta, et al., 2020).[2] Given that blockchains are well-suited for

[1] *PwC 2020 Global Blockchain Report*, PriceWaterhouseCoopers, October 2020.
[2] Some specific examples of how firms are using blockchain technology in these sectors include, e.g., "How Tesla and BMW are leading a supply chain renaissance with blockchain," *Forbes*, April 14, 2020; "Nexo and Mastercard launch

reducing the costs associated with information gathering and state verification, a natural question to ask is whether this new technology can enlarge the contracting space for counterparties, thereby helping to overcome problems arising from contractual incompleteness.

A key empirical difficulty in studying the effects of blockchain technology is that firms may endogenously choose to develop and use the technology in response to their contracting environments. Moreover, unobserved factors may be present that concurrently influence firms' contracting arrangements as well as their adoption of blockchain technology. To overcome these endogeneity problems, we use a novel quasi-natural experiment based on the staggered passage of U.S. state laws related to blockchain. From 2015 to 2019, 13 different states enacted legislation that lowered the cost of developing and using blockchain technology for in-state business and commerce. We investigate the causal effects of these plausibly exogenous shocks on not only firms' market value, but also their innovation activity, vertical integration, strategic alliance formation, and supplier-customer geography.

Our research design also exploits cross-sectional variation in the extent to which firms are vulnerable to contractual incompleteness. To capture firms' exposure to incomplete contracting problems, we construct a novel measure of asset specificity, namely, how difficult it is for a firm's assets to be adapted for use across multiple purposes or multiple contracting relationships.[3] We term this measure a firm's Asset Specificity Index (ASI). This measure is based on how textually dissimilar a firm's 10-K business description is from those of other firms. In contrast to other measures of relationship specificity or asset specificity that have been used in the literature (e.g.,

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'world first' crypto-backed payment card," *Reuters*, April 13, 2022; and "Mayo Clinic to use blockchain for hypertension clinical trial," *Healthcare IT News*, Sept. 7, 2022.

[3] In the presence of incomplete contracting, asset specificity is a key contributor to the classic "hold-up" problem and suboptimal levels of investment (see Williamson, 1975; Klein, Crawford, and Alchian, 1978; Grossman and Hart, 1986; and Hart and Moore, 1988, 1990).

Joskow, 1988; Ramey and Shapiro, 2001; Nunn, 2007; and Kim and Kung, 2017), our measure is both firm-specific and time-varying, enabling us to use triple-difference models to test the prediction that firms with higher ex ante exposure to incomplete contracting problems benefit more from the passage of a pro-blockchain law.

The first part of our analysis examines how firm valuations, measured by Tobin's Q, change upon the enactment of pro-blockchain laws in states where the firms do business.[4] In panel regressions, we find strong evidence that pro-blockchain laws have a more pronounced effect on Tobin's Q when a firm has a higher ASI. These results hold for both annual and quarterly data, and they are robust to controlling for firm fixed effects, year (or quarter) fixed effects, and firm characteristics such as size, performance, industry competition, cash holdings, and the degree of intangible assets and R&D in the industry. Furthermore, the estimated effects of ASI are economically significant. For instance, our estimates imply that, ceteris paribus, a treated firm with asset specificity at the 90th percentile experiences a post-law change in log-transformed Tobin's Q that is about 0.07 higher, or more than 6.5% of the sample mean, compared to a firm with asset specificity at the 10th percentile. Overall, these findings support the notion that pro-blockchain legislation is more beneficial to firms with greater ex-ante exposure to hold-up and incomplete-contracting problems.

Next, we explore the real effects of pro-blockchain legislative shocks on corporate innovation activity, including R&D intensity, patenting volume, market value, and the scientific focus of firms' patent applications. In panel regressions that account for potential sources of heterogeneity with time-varying firm controls, firm fixed effects, and year fixed effects, we find that firms with higher ASIs raise their R&D intensity and blockchain-related patenting more after

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[4] We use a firm's establishment-level sales, rather than its headquarters location, to ascertain whether the firm operates within a state in the year that the state enacts a pro-blockchain law (see Section 3 for details).

a new blockchain law. This suggests that high-ASI firms can benefit significantly from the new technology and that they attempt to capitalize on the passage of a pro-blockchain law by devoting more resources to blockchain-related innovation. Interestingly, we also find that firms with higher ASIs exhibit a greater reduction in the scientific generality of their patenting after a new pro-blockchain statute. This result is consistent with the idea that blockchain technology, by alleviating hold-up problems, can make it more worthwhile for a firm to focus on specialized innovations (which are more likely to represent relationship-specific investments) rather than pursuing only innovations with high generality.

Having found that asset specificity is an important moderator of the impact of blockchain laws on market valuations and innovation activity, we next examine how blockchain laws and asset specificity affect a firm's strategic decisions with respect to ownership and organization. Using panel regressions, we document that firms with higher ASIs exhibit larger declines in overall vertical integration as well as in vertical M&A dealmaking following a pro-blockchain law. This result is consistent with the view that blockchain technology provides a new, lower-cost alternative to vertical integration for solving the hold-up problem in incomplete contracting. We also find that, after the passage of a pro-blockchain law, firms with higher ASIs show a significantly greater increase in strategic alliance formation, more positive cumulative abnormal returns (CARs) around alliance deal announcements, and larger deal values. These findings support the notion that blockchain technology can alleviate hold-up problems that are commonplace in arms-length business collaborations, thereby relaxing constraints and enhancing the value of such deals.

In further tests, we examine the effects of blockchain laws and asset specificity on the geography of supplier-customer business ties. To the extent that blockchain technology enlarges the contracting space and alleviates hold-up problems, suppliers will no longer need to prioritize nearby customers to adequately monitor and gather information. Instead, suppliers can form new, more profitable business ties with a wider range of customers than before. We expect this effect to be more pronounced for high-ASI firms, namely, those that face more severe hold-up problems ex ante. In line with this prediction, we find that supplier firms with higher ASIs exhibit a greater shift away from local customers after the adoption of a pro-blockchain law. In addition, treated firms with higher ASIs are more likely to add distant customers after pro-blockchain legislation.

Our paper is related to literature that spans the fields of contracting, technology, and corporate strategy. First, our work contributes to a large stream of research that studies how institutional arrangements can help overcome inefficiencies and hold-up problems in buyer-seller relationships. Prior work in this area has argued that the classic hold-up problem arising from contractual incompleteness can be at least partially resolved through corporate governance arrangements, vertical integration, long-term contracting, or restrictions on parties' ability to renegotiate (see, e.g., Williamson, 1985; Williamson, 1988; Hart and Moore, 1990; Hart, 1995; and Maskin and Tirole, 1999). Our evidence suggests that blockchain technology can offer another useful solution to incomplete contracting problems—one that relaxes constraints and enhances opportunities without requiring costly changes to corporate organization.

We also contribute to the emerging literature that examines blockchain technology and its implications for commerce and contracting. Theoretical research has studied the economic underpinnings of blockchain technology (e.g., Chiu and Koeppl, 2017; Abadi and Brunnermeier, 2018; Biais et al., 2019) and how blockchain's decentralization features can affect competition and contracting in supplier-customer relationships (Cong and He, 2019), peer-to-peer crowdfunding markets (Li and Mann, 2018; Cong, Li, and Wang, 2021), and general digital platforms (Catalini and Gans, 2020).[5] We add to this literature by providing the first empirical evidence that state blockchain laws have significant causal effects on firms' market values and strategic policies. Moreover, our paper can offer novel insights to policymakers and practitioners seeking to understand how the widespread adoption of blockchain technology may impact contracting and commerce in the future.

Finally, our work is related to the broad literature that studies how firms adapt their innovation, investment, financing, and organizational strategies in response to changes in their environment. Much of the research in this area focuses on strategic responses to product-market threats, such as the market entry of competitors (Khanna and Tice, 2000; Goolsbee and Syverson, 2008), import tariff reductions (Fresard, 2010; Fresard and Valta, 2016), or increased import penetration (Lie and Yang, 2023). Other papers explore how firms use innovation strategies to respond to rivals' actions (e.g., Lerner, 1997; Hall and Ziedonis, 2001; Lo and Thakor, 2019; and Sampat and Williams, 2019). In contrast, we focus on a different type of shock to firms: the advent of a new digital technology. Our analysis spans many different industries and thus offers new insights into the role of corporate strategy amidst technological disruption. Furthermore, our finding that asset specificity matters greatly for how much a firm can benefit from blockchain technology underscores the importance of accounting for differences across individual firms' contracting environments.

The remainder of the paper is organized as follows. Section 2 develops hypotheses about the implications of blockchain technology and asset specificity for market valuations and other firm-

[5] Other papers have empirically explored the role of blockchain technology in specific applications such as Bitcoin markets (Easley, O'Hara, and Basu, 2019; Griffin and Shams, 2020) and Initial Coin Offerings (Howell, Niessner, and Yermack, 2020). In addition, survey papers have examined applications of blockchain technology to financial markets (Harvey, 2016) and corporate governance (Yermack, 2017).

level outcomes. Section 3 describes our data sources, details the construction of our ASI measure, and provides descriptive statistics on blockchain laws and firm characteristics. Section 4 describes our identification strategy. We present our results in Section 5. Section 6 concludes.

2. Hypothesis Development

As a form of decentralized ledger, blockchains possess two key characteristics that can help facilitate the contracting process between parties. First, blockchains can record transactions and information in a form that is immutable and highly transparent, thus dispensing with the need for third-party adjudicators and costly verification of state (Nakamoto, 2008; Chod et al., 2020). Second, blockchains make it possible to operate so-called "smart contracts," which are programs that reside on-chain that automatically run when predetermined conditions are met (Szabo, 1997). The self-executing nature of smart contracts enables blockchains to dramatically lower the costs of gathering and recording data in a wide variety of settings. Smart contracts can also facilitate decentralized consensus among agents by reducing the cost of disseminating information to parties across a network (Cong and He, 2019). Together, these core features—the capacity to permanently record information in a transparent way and to greatly reduce the costs of collecting and disseminating that information—make blockchain technology well-suited for improving the efficacy of contracting between firms.[6]

The degree to which parties can benefit from adopting blockchain technology will depend

[6] The potential benefits of blockchains notwithstanding, firms in practice likely face costs and challenges in implementing the technology. For example, because blockchains have finite scalability, growth in users and transactions can lead to higher fees, more congestion, and increased latency (Hafid, Hafid, and Samih, 2020; Chen, Cong, and Xiao, 2021; John, O'Hara, and Saleh, 2022; John, Rivera, and Saleh, 2022). The use of blockchains may also give rise to *ex post* dispute resolution costs due to unforeseen events or the inability of offline judicial authorities to correctly interpret smart contract code. Nevertheless, research suggests that new technological developments, such as layer-2 scaling solutions (Cong, Hui, Tucker, and Zhou, 2023) or dispute resolution schemes embedded in smart contracts (Schmitz and Rule, 2019), will be able to help firms in the future overcome many of the challenges associated with blockchain use.

on how exposed they are to problems arising from contractual incompleteness. As argued by Williamson (1975), Klein, Crawford, and Alchian (1978), and Grossman and Hart (1986), a major cause of value loss and inefficiency in contracting relationships is the so-called “hold-up” problem. Consider, for example, the setting of bilateral trade between a supplier firm and a customer firm. When the supplier’s assets are highly specific to its relationship with the customer, the supplier will have few outside options for selling its product. In such a scenario, the supplier will be reluctant to make sunk investments into the relationship due to the concern that, ex post, the customer will opportunistically “hold up” the supplier to capture a larger portion of the resulting surplus than was originally agreed upon.

Blockchain technologies can potentially help resolve hold-up problems in two important ways. First, by substantially lowering the costs of verifying whether parties have fulfilled their contractual obligations, blockchain-based smart contracts make it feasible for parties to write more complete contracts that cover broader sets of contingencies (Gans, 2019). With contracts that transparently specify parties’ obligations in more states of the world, supplier-customer relationships become less vulnerable to ex post opportunism and hold-up. Real-world applications of smart contracts to enrich the space of contractible contingencies in supply chains include, for example, a decentralized database of food provenance among growers, processors, distributors, and retailers; a blockchain-based system for coordinating shipments, invoicing, and payments in a distribution network; and a digital platform for the tracking and tracing of manufacturing parts.[7]

Second, blockchains can alleviate hold-up problems by helping to prevent parties from renegotiating their initial agreements. As established in the theory of incomplete contracts,

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[7] See, for instance, “Mastercard partners with GrainChain for blockchain food traceability,” *Ledger Insights*, Oct. 29, 2020; “How Walmart Canada Uses Blockchain to Solve Supply-Chain Challenges,” by K. Vitasek et al., *Harvard Business Review*, Jan. 5, 2022; and “Samsung Joins Blockchain Bandwagon to Manage its Supply Chain,” *HT Tech*, Aug. 19, 2022.

renegotiation is a key enabler of ex post opportunism: it is only when parties cannot commit not to renegotiate that the threat of hold-up arises (Hart and Moore, 1988; Rogerson, 1992). Therefore, commitment mechanisms that limit ex post renegotiation can help deter hold-ups and foster efficient investment. Smart contracts serve as one such commitment device since they are self-executing, immutable, and transparent to contracting parties (Meier and Sannajust, 2021). Furthermore, smart contracts can be used to establish liquidated damages—penalties that are triggered if a specific breach of contract occurs. By designing smart-contract penalty clauses so that imposed damages cannot be enjoined, avoided, or reversed by courts, counterparties can create a strong commitment mechanism that deters renegotiation of their earlier contractual agreements (Holden and Malani, 2021).

The above logic leads to straightforward predictions about how firms' values and innovation policies will change in response to a reduction in the costs of using blockchain technology. For instance, when a state pro-blockchain law removes obstacles to the use of blockchains in commerce, it is those firms with high asset specificity that stand to gain the most value from the law change and that hence will invest more of their own resources in developing the technology. We therefore expect that firms with higher asset specificity will respond to a pro-blockchain law with larger increases in their innovation inputs (research and development) as well as larger increases in the volume of their innovation output. Furthermore, under the assumption that blockchain technology helps safeguard against hold-up and inefficiency problems, high asset-specificity firms will exhibit a greater shift away from general innovations and towards more valuable, albeit more specialized, innovations.

Blockchain technology also has implications for vertical integration activity among firms. A large literature explores how corporate transactions that bring productive activity under one roof, such as vertical mergers and acquisitions (M&A), can align incentives and alleviate the hold-up problem (Grossman and Hart, 1986; Hart and Moore, 1990). Yet, vertical integration itself is costly because it leads to larger and more complex organizations, loss of control for counterparties, and the need to integrate different cultures and workforces (Whinston, 2003; Joskow, 2008). To the extent that blockchains can solve hold-up problems at a relatively low cost without causing organizational disruption and loss of autonomy, firms may turn to blockchain technology rather than pursue vertical integration. Thus, we hypothesize that, with the passage of a pro-blockchain law, vertical integration activity should decline, particularly among firms with a high degree of asset specificity.

Apart from its effect on vertical integration, blockchain may also influence the formation of strategic alliances between firms. Unlike M&A deals that dramatically alter the boundaries of firms, strategic alliances are arms-length, non-integrative arrangements that do not directly solve the underinvestment and ex post hold-up problems. In fact, alliances themselves can give rise to severe hold-up problems because they often require the exchange of hard-to-specify assets and resources, such as scientific knowledge and research effort (Pisano, 1990; Robinson and Stuart, 2007; Lerner and Malmendier, 2010). Based on this consideration, we hypothesize that blockchain technology will lessen the costs of strategic alliances and cause firms with high ex ante asset specificity to pursue a greater number of such deals.

Blockchain technology may also lead to changes in the geography of supplier-customer relationships. In the absence of complete contracting, a traditional means for suppliers to facilitate trade is to choose customers that are in close geographic proximity. Proximity in a supplier-customer relationship can enable both parties to share real-time information about each other's demand, willingness to pay, and ongoing performance in meeting contractual obligations.[8] Given the inherent advantages of geographic proximity for information gathering, performance monitoring, and contract enforcement, many supplier firms will simply avoid forming business ties with non-local customers. However, this geographic constraint will become less binding to the extent that firms can adopt and use blockchain technology. We thus expect that state laws that lower the costs of using blockchains in commerce should lead supplier firms to expand their business dealings to less geographically proximate—but more valuable—customers. Moreover, this shift towards less proximate customers should be especially pronounced when suppliers' asset specificity is high.

3. Data

In this section, we provide details on the sample of state pro-blockchain laws and describe our data sources for firms' geographic footprints, financial information, innovation activities, vertical integration, strategic alliances, and supplier-customer relationships. We also outline the steps used to construct our text-based measure of firms' asset specificity.

3.1. State Pro-Blockchain Legislation

We manually collect information on all state-level legislation bills enacted by the end of 2019 that relate to blockchain or distributed ledger technologies. Our data source for this information is the "Blockchain State Legislation" collection published by The National Conference of State Legislatures (NCSL), an association of nonpartisan public officials that is

[8] Prior research has documented empirically that, in many economic settings, geographic proximity facilities access to valuable knowledge and soft information. See, for example, Jaffe, Trajtenberg, and Henderson (1993), Audretsch and Feldman (1996), Coval and Moskowitz (2001), Malloy (2005), Mian (2006), Butler (2008), Agarwal and Hauswald (2010), Granja, Matvos, and Seru, (2017), and Bray, Serpa, and Colak (2019).

composed of sitting state legislators and that "represents the legislatures in the states, territories and commonwealths of the U.S."[9] We review summaries of all blockchain-related laws from the NCSL website and confirm all the included laws pertain to blockchains, distributed ledgers, smart contracts, or cryptocurrency. Although many legislation bills are evidently favorable to the general use of blockchain, some are neutral or even contain restrictions on blockchain usage.[10] We exclude the neutral or unfavorable bills from the sample. For the set of legislation bills that remain, we gather additional information from state legislation websites and from LegiScan (www.legiscan.com) on the most current stage of the bill, the date when it was first introduced into a state's legislative session, and the date (if any) on which it was enacted into law by the governor's office.[11] We retain all bills that were enacted by the end of 2019. This step yields 41 pro-blockchain legislation bills that were enacted by 20 states.

Next, we review the summaries of these legislation bills and exclude any bills that are not specifically favorable to the use of blockchain in private-sector business and commerce and, thus, are not directly related to resolving contractual incompleteness for firms. In particular, we exclude (1) bills for which the summary only mentions virtual currency;[12] (2) bills that pertain exclusively

[9] The website of the NCSL is https://www.ncsl.org/aboutus.aspx. The Blockchain State Legislation Collection is available at the following links: https://www.ncsl.org/research/financial-services-and-commerce/blockchain-2019-legislation.aspx#2019Legis and https://www.ncsl.org/research/financial-services-and-commerce/the-fundamentals-of-risk-management-and-insurance-viewed-through-the-lens-of-emerging-technology-webinar.aspx (Last accessed on December 13, 2022).

[10] For example, West Virginia 2018 House Concurrent Resolution 29 requests a study on "Bitcoin, its future and potential impact on the state, its citizens, and businesses" and is thus neutral to blockchain. California 2017 AB 1123 appears to be restrictive to blockchain usage as it "requires persons to gain licensure and approval to engage in any virtual currency business."

[11] When the legislation website does not mention a date on which a bill is "first read," we use the date on which it was "introduced." For example, for Wyoming 2018 House Bill 70, we use Feb. 13th, 2018 because it is shown as the date when the bill was first "Introduced and Referred."

[12] Examples include Illinois 2017 Senate Bill No. 868, which concerns including "virtual currency in [the] revised Uniform Unclaimed Property Act," and New Hampshire 2017 House Bill No. 436, which aims at exempting "persons using virtual currency from being licensed as money transmitters."

to the use of blockchain by the state government;[13] (3) bills related solely to corporate record-keeping (e.g., tracking stockholders of record);[14] and (4) bills which advocate for the development of blockchain technology but do not directly lower the costs of using blockchain in commerce.[15] Using the websites of state legislatures, we download and review the full texts of candidate bills to confirm that the texts are consistent with the summaries.

[Insert Table 1 Here]

Our final sample consists of 16 pro-blockchain state legislation bills enacted by 13 different states through 2019.[16] Each of these bills includes specific provisions designed to facilitate the adoption and use of blockchain technology in private-sector commerce. Table 1 lists these laws and provides information on each law's adopting state, bill number, date of first introduction to a legislative session, date of enactment, and a summary of core provisions. Although the bill provisions differ in how they specifically pertain to blockchain, they can be roughly grouped into the following types: (1) provisions that prohibit local government from taxing, impeding, or restricting persons who use blockchain technology in commerce; (2) clauses that legitimize the use of smart contracts in business (e.g., by giving them legal status equivalent to pen-and-paper contracts); (3) revisions to the Uniform Electronic Transaction Act (UETA) to allow for

[13] For instance, Colorado 2018 Senate Bill No. 86 pertains only to the Colorado Department of State's use of distributed ledger technology for records and data management, and Wyoming 2019 House Bill No. 70 authorizes the Secretary of State to develop and use a blockchain filing system. (Note: the Wyoming 2018 House Bill No. 70, which is included in our sample, is distinct from the 2019 bill despite the fact that they share the same bill number.)

[14] E.g., California 2018 Senate Bill No. 838 calls for the authorization of companies' use of blockchain for keeping track of stockholder ownership and transfers.

[15] For example, Arizona 2019 House Bill No. 2747 calls for the development of a blockchain research center.

[16] Because the sample period in our main tests extends to 2021, we also reviewed blockchain-related legislation bills on NCSL that were enacted in 2020 or 2021. Among all blockchain-related bills signed into law in these two years, only the Washington 2020 Senate Bill No. 6028 fulfills our requirement of being favorable to the use of blockchain in private-sector business and commerce. It is unlikely that including the Washington 2020 Senate Bill No. 6028 would materially affect our empirical results given that (1) our sample already includes the Washington 2019 House Bill No. 70 and (2) the treatment indicator in our panel regressions captures the occurrence of a law event in the prior three years.

transactions recorded by a blockchain;[17] and (4) protections for ownership rights with respect to information secured on a blockchain. The earliest passed bill in our sample is Vermont House Bill No. 868, introduced in March 2016 and signed by the governor in June 2016, while the latest is Illinois House Bill No. 3575, introduced in February 2019 and enacted in August 2019. Our empirical strategy requires being able to identify which firms operate within or outside of a state at the time of a legislative shock. As described in Section 3.2 below, we accomplish this using historical data on the geographic locations of firms' establishments.

3.2. Geographic Footprints

To ascertain the geographic locations of where firms do business, we rely on information from Data Axle (formerly known as InfoGroup). Data Axle is a large database that reports annual information on the physical locations of millions of U.S. businesses.[18] Its coverage starts from 1997 and extends to the present. The information in Data Axle is compiled using identification and location data from U.S. yellow page directories, phone verification, and public resources such as websites, news stories, and annual reports. Included in Data Axle is information on the organizational hierarchical position of an entity within its corporate family. Thus, each entity is identified as a parent location, a subsidiary location, or a branch location. In addition, to the extent possible, each entity is associated with the value of sales and the number of employees at that location. For each corporate family, Data Axle provides various identifiers that reflect parent-subsidiary-branch relationships. We make essential use of these identifiers to conduct a name-

[17] UETA is an act published by the Uniform Law Commission in 1999 that gives electronic signatures equivalent legal effect as handwritten signatures under the statute of frauds. Including transactions recorded on a blockchain into UETA legitimizes the use of blockchain-based transactions by making them more like other electronic transactions.

[18] More information on this data source is available at the provider's website https://www.data-axle.com/, and data guides can be found at https://platform.data-axle.com/places/docs. An overview of Data Axle is also available from Wharton Research Data Services (WRDS): https://wrds-www.wharton.upenn.edu/pages/support/manuals-and-overviews/infogroup/wrds-overview-infogroup/#coverage-and-data-quality.

based data merge between Data Axle and Compustat. Part A1 of Appendix A provides details of our name-based matching procedure.

3.3. The Asset Specificity Index (ASI): A Measure of Exposure to Hold-Up Problems

To gauge the extent of an individual firm's asset specificity, we construct a firm-specific and time-varying measure based on the textual business descriptions in "Item 1" of firms' 10-K filings. For each firm in a given year, we calculate the average textual similarity between the firm's business description and the five most similar business descriptions among other contemporaneous firms. One minus this average similarity is what we define as the focal firm's *Asset Specificity Index* (*ASI*). This measure captures the idea that a firm with a more distinctive and unique business description has more relationship-specific assets and hence is more prone to hold-up problems.

Our measure is related to a well-known input specificity measure ("contract intensity") introduced by Nunn (2007).[19] Nunn's measure is constructed as $Z_i = \sum_j \mathrm{w}_{ij} {R_j}^{neither}$, where w_{ij} is the value of input j used in industry i, divided by the total value of inputs used in industry i, and ${R_j}^{neither}$ is the percentage of input j that is neither sold on an organized exchange nor reference-priced. The construction of Nunn's measure is based on the 1997 United States I-O Use Table, which identifies intermediate inputs and the production of each final good. Hence, by design, this measure is an industry-level summary measure of contracting intensity.

While firms in high-specificity industries as per Nunn's measure very likely face more severe hold-up and underinvestment problems than other firms, this measure is not able to capture time-varying, cross-firm differences in specificity within a given industry. Other asset specificity measures used in the literature (e.g., the measures of Feenstra, 1996, and Rauch, 1999, used in

[19] For more details, see https://scholar.harvard.edu/nunn/pages/data-0

Barrot and Sauvagnat, 2016) face a similar aggregation issue because they are defined for entire industries rather than for individual firms. A further difficulty with using Nunn's measure for our purposes is that it mainly focuses on manufacturing and excludes other important sectors (e.g., retail trade, wholesale trade, technical services, education, and healthcare). For these reasons, we develop our own firm-year-level measure of asset specificity while building upon Nunn's (2007) idea of capturing specificity in terms of the uniqueness of commodities that link different industries with each other.

The construction of our asset specificity index (ASI) starts with Compustat firms' 10-K "Item 1" business descriptions obtained from the SEC Edgar website.[20] Since 10-K filing contents are subject to federal regulations,[21] the relevancy and accuracy of their business descriptions are the responsibility of the reporting firm. This helps to ensure that our constructed measure has adequate informativeness and relevance. From a technical perspective, our measure shares commonalities with the 10-K Text-based Network Industry Classifications (TNIC) measure developed by Hoberg and Phillips (2010, 2016).[22]

Next, we convert each business description to a word vector and use Term Frequency-Inverse

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[20] We identify the paths to 10-K filings using the Master Index files distributed by the SEC. We use the Python API "SEC-API" version 1.0.12 to complete the extraction of the business description section. We remove the xml and html tags from the extracted texts using Python library "Beautiful Soup" version 4.11.1. We then exclude extractions smaller than 800 bytes because the filing firms of those are mostly exempted from the required disclosure of "Item 1." In virtually all such cases, the extracted texts are either blank or simply state that the section is not required.

[21] Specific requirements for the business description section are detailed in §17 CFR 229.101 (Section 229.101 of Title 17, Code of Federal Regulations, which can be viewed at https://www.ecfr.gov/current/title-17/chapter-II/part-229/subpart-229.100/section-229.101).

[22] Our handling of texts and construction of word vectors are not simply step-by-step replications of the procedure that Hoberg and Phillips use to construct their TNIC measure. There are two methodological differences. First, our asset specificity measure is not limited to a firm's product space; we deem the descriptions of business practices other than a firm's products as informative. Second, the authors recommend using Python "add ins" if a researcher needs alternative ways of rebuilding the pairwise textual similarity. Further details are available via the Hoberg-Phillips Data Library, accessible at http://hobergphillips.tuck.dartmouth.edu/industryclass.htm. See the documentation file "How2Build_orDownloadTNICdata.txt" in the zip folder hyperlinked to the part entitled "Download larger TNIC Database (calibrated to be as granular as two-digit SIC codes) [Good for projects needing more granularity]."

Document Frequency (TF-IDF)[23] to numerically represent the business description. Specifically, for firm j, we calculate a "business description vector" B_j in which the i^{th} element is equal to

$$b_{i,j} = frequency_{i,j} * \log_2 \frac{num\_docs}{document\_frequency_i}, \qquad (1)$$

where $frequency_{i,j}$ is the number of occurrences of term i in document j, num_docs is the total number of documents in the corpus, and $document\_frequency_i$ is the number of documents that contain the term i. Then, having constructed business description vectors for each firm in each year t of the sample, we can calculate a pairwise similarity between two firms i and k, denoted $S_{i,k,t}$, as the cosine similarity between the two firms' business description vectors.

For each firm i in year t, we calculate its pairwise similarity vis-à-vis every other firm in year t. We then take the five highest similarities for firm i, calculate the average, and subtract the average from one. The result is our Asset Specificity Index (ASI) for firm i in year t. In other words, we calculate firm i's ASI in year t as:

$$ASI_{i,t} = 1 - \overline{S_{i,k,t}} \ , \qquad (2)$$

where $S_{i,k,t}$, $k = 1, 2, \ldots, 5$ are the five highest pairwise similarity scores between firm i and other firms in year t.

[Insert Table 2 Here]

Table 2 provides descriptive statistics for the constructed asset specificity index. Among all 2-digit NAICS sectors, the one with the highest average ASI is Agriculture, Forestry, Fishing, and

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[23] We use the Python library "Gensim" (Version 4.2.0) to pre-process the extracted business description texts. For each year, after removing stop words and single-character terms from each extracted text, we build a corpus of tokenized business descriptions, i.e., business descriptions in the form of bags of words. Here, "year" is the calendar year in which a firm's fiscal year ended. We specify stop words as the English common stop words defined by NLTK, plus "item 1" and "business". A corresponding vector of words is then constructed based on the corpus. Each element of this vector is assigned to a specific term that has appeared in at least 10 but not more than 80% of the extracted business descriptions in that year. The maximum length of the vector is set as 70,000. In the vector of a given business description document, the value of each element is the TF-IDF weight of the term in that document. Documentation of the TF-IDF model: https://radimrehurek.com/gensim/models/tfidfmodel.html#gensim.models.tfidfmodel.df2idf.

Hunting (NAICS code 11), followed by Professional Services (NAICS code 54) and Wholesale Trade (NAICS code 42). Sectors with the lowest asset specificity are Educational Services (NAICS code 61), Mining, Quarrying, and Oil and Gas Extraction (NAICS code 21), and Accommodation and Food Services (NAICS code 72). This ranking differs substantially from that implied by Nunn's (2007) measure. For instance, according to Nunn's measure, Information (NAICS code 51) has the highest specificity, Agriculture, Forestry, Fishing and Hunting, and Manufacturing (NAICS codes 31-33) are ranked in the middle, and Utilities (NAICS code 22) and Mining, Quarrying, and Oil and Gas Extraction are ranked at the bottom.

Since we use the full text of "Item 1" to calculate text similarity, one potential concern about our ASI measure is that it might, to some extent, capture information about a firm's products rather than its assets. To address this issue, we construct an alternative ASI measure based on purged Item 1 business descriptions and find similar results (see Section 5.3 for details).

3.4. Financial and Organizational Data

We obtain firms' stock market information (price per share and shares outstanding) and other financial variables (e.g., total assets, book value of common equity, net income, cash holdings, R&D, sales, and intangible assets) from the CRSP/Compustat merged database.

To capture firms' patenting activities, we download the "Patent Application Full Text Data" and "Patent Grant Bibliographic (Front Page) Text Data" from the United States Patent and Trademark Office (USPTO) Bulk Data Storage System (BDSS)[24]. We extract information on the

[24] USPTO bulk data are available at https://bulkdata.uspto.gov/. Prior research has used these data indirectly to obtain information on applications, grants, assignees, and inventors (see, for example, Kogan, Papanikolaou, Seru, and Stoffman, 2017; Brav, Jiang, Ma, and Tian, 2018; Bernstein, McQuade, and Townsend, 2021; Li and Wang, 2022). Other research has used USPTO bulk data for the purpose of conducting text-based analysis to identify and classify specific types of innovation, e.g., FinTech patents (Chen, Wu, and Yang, 2019) or green patents (Cohen, Gurun and Nguyen, 2020).

application date, publication date, citations, assignee name, location, and International Patent Classification (IPC) codes. To merge the patent applications data to our Compustat sample through Data Axle, we develop a multi-step approach that involves string matching, the application of various machine-learning algorithms, and additional manual checks. Details of the various steps involved in this merging process are given in Part A2 of Appendix A. We then link the patent applications in our sample to patent grants data to identify applications that are eventually granted.

To identify patent applications that are specifically related to blockchain, we assemble a lexicon of blockchain-related terms and use it to conduct text-based filtering of the overall sample.[25] We also construct a measure of how general a firm's innovation activity is in a given year. Following prior literature (e.g., Hall, Jaffe, and Trajtenberg, 2005; Hsu, Tian, and Xu, 2014) we define a patent's generality to be one minus the Herfindahl Index of the distribution of three-digit IPC codes across all the patents that cite it. A firm's innovation generality is then defined as the average of patent generality across all patents filed by the firm during the year.

To measure firms' overall vertical integration, we use the firm-year specific vertical integration scores developed by Frésard, Hoberg, and Phillips (2020), which are computed based on text similarities between the business description in firms' 10-K filings and language in the commodity descriptions for the 2002 BEA Input-Output (IO) tables. We obtain the data from the "Fresard-Hoberg-Phillips Vertical Relatedness Data Library".

We gather information on M&As and alliance deals from the Thomson Reuters SDC database. Aggregate deal activity for each firm is computed at the fiscal-year level. Firm-years with no M&A/alliance deals reported in the SDC Platinum database are counted as zero. Since we use industry information to identify vertical integration among M&A deals, we require that both

[25] The collection of blockchain terms and further details about how we use it to filter patent applications are provided in Part A of the Internet Appendix.

the target and the acquirer are U.S. public firms included in the CRSP/Compustat merged database.[26] In the case of alliances, we include only deals for which at least one participant is a U.S. public firm and contained in the CRSP/Compustat merged database.

To capture the degree of vertical relatedness for M&A deals, we employ the Bureau of Economic Analysis (BEA) 2012 United States I-O Use table, which identifies intermediate inputs and the production of each final good at the industry level. We merge the data to our firm-level data using the industry code mapping between the BEA industry classification and NAICS. We start with 5-digit NAICS matching. If the 5-digit NAICS are not matched, we then attempt to match at the level of 4-digit NAICS codes. If 4-digit codes do not result in a match, we then attempt to match at the 3-digit NAICS level.

To investigate the geography of ties between suppliers and their customers, we follow previous studies[27] and use information from the Compustat Historical Segments data to identify supplier-customer business ties. The dataset provides business and geography details, product information, and customer data for over 70% of the companies in the Compustat North American (NA) database. Companies are required to report information on their major customers under the Financial Accounting Standards Board (FASB) Statement of Financial Accounting Standards (SFAS) No. 131 and under rules put forth by the Securities and Exchange Commission (SEC).

We build our initial sample of supply-chain ties by extracting all supplier-customer pairs from the Historical Segments dataset for the period from 2010 to 2021. We merge these pairs to

[26] Following common practice in the literature, we also employ several basic screening conditions for M&A deals: (1) the value of the transaction is not less than one million U.S. dollars; (2) the percentage of shares the acquirer is seeking to own after the transaction is larger than 50%, while the percentage of shares acquired held before the announcement is less than 15%; (3) both the target and the acquirer have industry identifiers available; and (4) the form of the deal defined by SDC is "merger, acquisition of majority interests, and acquisition of assets".
[27] See, for example, Fee and Thomas (2004), Fee, Hadlock, and Thomas (2006), Kale and Shahrur (2007), Banerjee, Dasgupta, and Kim (2008), Cohen and Frazzini (2008), Hertzel, Officer, and Rodgers, (2008), Raman and Shahrur (2008), Barrot and Sauvagnat (2016), Cen, Maydew, Zhang, and Zuo (2017), Chu, Tian, and Wang (2019).

the main Compustat data using the WRDS Supply Chain with IDs data, supplemented by our own name-matching procedures as documented in Part A3 of Appendix A. Each firm pair contains a supplier and customer and reflects the direct business link between the two for the reporting year. For suppliers that report more than one major customer in the same year, we construct multiple pairs so that each pair includes the supplier and one of its customers. We require that all paired firms are headquartered in the United States and have available CRSP/Compustat data. From this sample, we further exclude exchange-traded funds (ETFs) and trusts managed by operating financial entities. We rely on the zip codes of headquarters and use the centroids of zip codes to calculate the geodesic distance for each supplier-customer pair.

3.5. Summary Statistics

To conduct our analysis, we extract firm-year observations from CRSP/Compustat for the period 2011-2021. We then merge the resulting panel dataset to Data Axle and to our data on state legislation bills to identify treated firms and the control group. Table 3 presents summary firm and industry statistics for the panel dataset. Further details on the construction of key variables are given in Section 5, and Appendix B provides a list of variable definitions.

[Insert Table 3 Here]

In our sample, the mean and median of yearly Tobin's Q (log-transformed) are 1.07 and 0.94, respectively. On average, a hundred firms file about 4.5 blockchain patents in a given year. The average patent generality score is 0.08. The incidence of all M&A deals and high vertical relatedness deals is 3.2% and 2.1%, respectively. Alliance deals are more frequent than mergers: on average, firms undertake 0.34 alliance deals, 0.26 strategic alliance deals, and 0.18 strategic high-tech strategic alliance deals each year. Each firm, on average, has 0.25 (0.28) nearby corporate customers headquartered within 50 (100) kilometers, and the average distance between the supplier and the customer in a given pair is 1,511 kilometers. The average size of firms in our sample, as measured by the log of total assets, is 6.73. The mean and median return on assets is, respectively, -0.05 and 0.02. The mean level of industry weighted-average intangible assets (log transformed) of an industry is 8.12, the mean of industry weighted-average R&D (log-transformed) is 4.02, and the mean industry concentration ratio (as measured by HHI) is 0.24.

4. Identification Strategy

We examine the effects of pro-blockchain legislation using a staggered difference-in-difference-in-difference (DDD) framework. This approach has been used previously to investigate the effects of law enactments, policy changes, or other types of exogenous shocks (e.g., Gruber and Poterba, 1994; Giroud and Mueller, 2010; Puri, Rocholl, and Steffen, 2011; Jens, 2017; Borochin and Yang, 2017). Our main question of interest is whether pro-blockchain laws have heterogeneous effects on firms, i.e., effects that vary with a firm's asset specificity (which proxies for ex-ante exposure to incomplete contracting problems). To address this question, we use firm-year level data from 2011 to 2021 to estimate panel regressions of the following form:

$$Y_{it} = \alpha + \beta_1 Post\ Treat_{it} \times ASI_{it} + \beta_2 Post\ Treat_{it} + \beta_3 Treat_i \times ASI_{it} + \beta_4 ASI_{it} + \gamma_1 Z_{it} + \eta_i + \xi_t + \epsilon_{it}, \tag{3}$$

where the main explanatory variable is the interaction term $Post\ Treat_{it} \times ASI_{it}$. $Post\ Treat_{it}$ is an indicator equal to one if at least one pro-blockchain legislation bill has been passed in the past three years in states where firm i operates (i.e., states for which the firm has non-missing, non-negative sales in Data Axle).[28] ASI_{it} is the measure of asset specificity for firm i in year t.

[28] In untabulated robustness tests, we change the definition of $Post\ Treat_{it}$ to indicate that at least one pro-blockchain legislation bill has been passed in states where firm i operates, and our results are consistent. In separate, untabulated tests, we restrict treated firms to those that have at least 1% of total sales (the sum of all non-missing state sales) in a treated state, and we obtain similar results.

$Treat_i \times ASI_{it}$ is the interaction term of $Treat_i$ and ASI_{it}, where the former indicates that firm i experiences at least one pro-blockchain law during the sample period. The outcome variable of interest, Y_{it}, corresponds to a measure of firm value or a particular corporate policy. We control for various firm and industry characteristics Z_{it} and include firm fixed effects, η_i, and year fixed effects, ξ_t, in the regressions.

Within the staggered DDD framework presented in equation (3), $Post\ Treat_{it}$ picks up the difference-in-difference effect between the control and the treated group due to the passage of the pro-blockchain laws. The interaction term, $Post\ Treat_{it} \times ASI_{it}$, estimates the third difference, that is, whether the legislation has different effects on in-state firms with different levels of asset specificity. The regression also controls for stand-alone variables, including $Post\ Treat_{it}$, $Treat_i \times ASI_{it}$, and ASI_{it}. Note that we do not separately control for $Treat_i$ because it is absorbed by the firm fixed effects.

The staggered DDD design exploits two types of variation: (1) differences between treated and control firms with respect to changes in firm values (or corporate polices) induced by legislative events; and (2) cross-sectional variation in firms' asset specificity. The adoption of plausibly exogenous shocks to the costs of using blockchain in-state mitigates concerns about reverse causality. Moreover, the pro-blockchain laws in our sample are at the state level and are enacted at different times. Thus, the control group at year t includes both (1) firms that operate in states that never pass a pro-blockchain law during the sample period; and (2) firms that operate in states that do pass a law but at some point in time after year t. This design feature helps address concerns that the effects we document simply reflect persistent differences between states that never pass a pro-blockchain law (during the sample period) and states that have done so.

We acknowledge that more than half of the legislation bills in our sample were enacted in

2019. This concentration of events in 2019 might somewhat limit the degree of variation we can exploit in the timing of law enactments. However, we note that the variation in our setting comes from both the staggered nature of pro-blockchain laws and the within-state heterogeneity in firms' ASIs. Moreover, to better capture differences in the timing of law enactments, we also conduct our firm value tests using data at both annual and quarterly frequencies. Our results are qualitatively robust to the use of quarterly data rather than annual data.

Recent work by Goodman-Bacon (2021) and Baker, Larcker, and Wang (2022) points out that staggered difference-in-differences (DID) estimators, which are widely used in empirical finance research, can be biased and can result in incorrect inferences. The main cause of this bias is that the estimator depends partly on a comparison between the later-treated and earlier-treated observations, with the earlier-treated ones serving as controls. To confirm that our results are not driven by this type of estimation bias, we conduct robustness tests using stacked regressions as suggested by Baker et al. (2022) and as used in prior studies such as Gormley and Matsa (2011). Specifically, for each blockchain legislation event, we include a clean control group and a treated group. The clean control group consists of firm-year observations that have not yet experienced any pro-blockchain legislation as of a given year t plus firms that never experience any event during the sample period. The treated group consists of firms that experience the relevant state-level pro-blockchain legislation. If a firm is impacted by more than one adopted pro-blockchain law during the sample, the firm is only included in the treated group if the relevant legislation is the first such law experienced by the firm. We construct an event-specific identifier and stack together the event-specific datasets. A DDD regression is then estimated with firm × law fixed effects and year × law fixed effects.

5. Results

5.1. Firm Value Surrounding Blockchain Legislation

To set the stage for our main analysis, we first examine the joint effects of ASI and pro-blockchain laws on firm value as captured by Tobin's Q. We measure Tobin's Q as the ratio of the market value of equity (Compustat items PRCC_F × CSHO), plus total assets (Compustat item AT), minus the book value of common equity (Compustat item CEQ), to total assets. For robustness, we also construct an alternative measure of Tobin's Q following previous literature (Fazzari et al., 1988; Erickson and Whited, 2012): the ratio of the book value of debt (Compustat items DLTT + DLC), plus the market value of equity (Compustat items PRCC_F × CSHO), minus the firm's current assets (Compustat item ACT), to the book value of property, plant, and equipment (Compustat item PPEGT).[29] The alternative Tobin's Q measure has been widely used in recent literature, and it explains corporate investment well (Erickson and Whited, 2012). In constructing this alternative measure, to avoid distortions in which the Tobin's Q calculation involves dividing by a very small number, we exclude observations for which the annual PPEGT is less than $5 million. We use log-transformed Tobin's Q measures in the main tests because the raw measures are substantially skewed in our sample. In untabulated robustness tests, we use raw measures and obtain similar results.

Before conducting our main analysis, we provide a graphical depiction of the relationships between Tobin's Q, asset specificity, and exposure to a pro-blockchain law. Specifically, we run a regression of Tobin's Q on control variables and a set of triple interaction terms, each involving a yearly indicator (relative to the legislation event year), a *Treated* dummy, and a "high ASI"

[29] The main measure and the alternative measure of Tobin's Q are thus calculated using Compustat items as (PRCC_F × CSHO + AT – CEQ) / AT and (DLTT + DLC + PRCC_F × CSHO – ACT) / PPEGT, respectively.

indicator equal to one if the firm's ASI is above the sample median ASI.[30] We use the fiscal year ending within one year before the law enactment date as the baseline year, and we include indicators for each year up to three years before and three years after the baseline year. The effects of a pro-blockchain law enactment on firms with high-versus-low ASIs can be visualized by plotting the estimated triple interaction coefficients for different years. As seen in Figure 1, for firms impacted by a given pro-blockchain law, the marginal effect of having a high ASI on Tobin's Q is significantly positive in the years after the law enactment. The coefficients on the triple-interaction terms for the three years before the event are not significantly different from each other, which supports the identifying assumption in our setting that the outcome between high-ASI and low-ASI firms exhibits parallel trends between treated and non-treated states (see Olden and Møen, 2022).

[Insert Figure 1 Here]

Next, we move to the triple-difference panel regression setup specified in Equation (3), Section 4. If blockchains serve to mitigate problems from incomplete contracting, firms that face more severe hold-up problems (i.e., firms with higher ASIs in our setting) are expected to benefit more from adopting blockchain technology. Since the enactment of pro-blockchain laws can reduce legal concerns and uncertainty for in-state users of the technology, we expect in-state firms with higher ASIs to experience a larger post-enactment value improvement compared to non-treated firms. Columns (1) and (2) in Table 4 present the regression results for the two Tobin's Q measures. Along with firm and year fixed effects, we control for time-varying firm characteristics,

[30] For each pro-blockchain law adoption, we construct a legislation-specific sample consisting of a treated group and a control group. Included in the treated group are firms that experience the given event as their first time pro-blockchain law exposure. Firms that have not yet or never experienced any pro-blockchain legislation in our sample period are in the control group. For both groups, we keep firm-year observations from three years before to three years after the legislation event in the regression. We do so for all legislative events in our sample and stack these legislation-specific samples together to form the full legislation-firm-year sample to run the regression.

including firm size, ROA, cash holdings, and sales. We also control for industry average intangible assets, industry average R&D expenses, and HHI, all at the NAICS 5-digit level. Consistent with our prediction, we find that the coefficient on the main explanatory variable, $Post\ Treat \times ASI$, is positive and significant at the 1% level in both specifications. The results are also economically significant. Column (1), for instance, shows that an increase of ASI from the 10th percentile (0.28) to the 90th percentile (0.73) translates into an increase of about 0.07 in log-transformed Tobin's Q, or more than 6.5% of the sample mean. The regression also indicates that firms with an average ASI (which is 0.53 in our sample) or greater experience a net gain in Tobin's Q from pro-blockchain legislation.

[Insert Table 4 Here]

Because the majority of the law bills in our sample were passed in 2019, a possible concern with our findings is that they may reflect confounding shocks in 2019 rather than the causal impact of blockchain laws. In Columns (3) and (4), we address this concern by conducting similar tests as in Columns (1) and (2) but using firm-quarter data instead of firm-year data. As shown by the coefficients on the main explanatory variable, high-ASI firms exhibit greater increases in firm value compared to low-ASI peers and to the control group. The results again confirm that firms facing potentially severe hold-up problems are likely to benefit more than other firms from the advent of blockchain technology.

5.2. Blockchain Legislation, Asset Specificity, and Firms' Policy Responses

In this section, we consider the real effects of pro-blockchain laws and investigate how these effects are moderated by firms' ex ante exposure to incomplete contracting problems.

5.2.1. Innovation Activity

We first examine whether, in accordance with straightforward intuition, the passage of a blockchain law leads to a greater change in innovation activities for high-ASI firms. We begin with yearly R&D intensity, calculated as R&D expenses over sales. We keep missing values of R&D expenses as missing when constructing the variable. The results, reported in Column (1) of Table 5, are in line with our prediction from Section 2: the coefficient on $Post\ Treat \times ASI$ is positive and statistically significant, indicating that higher-ASI firms increase their R&D intensity more aggressively after being exposed to a pro-blockchain law.

[Insert Table 5 Here]

Since R&D intensity is an aggregated measure that reveals little information about the priorities and resulting outputs of firms' innovation activities, we use data on patent applications to examine more closely the effects of blockchain legislation. We identify blockchain-related patents by compiling lists of blockchain-related terms and applying them as a text-based filter to the set of all patent applications announced from 2011 to 2021.[31] We then form a dependent variable equal to either the number of all patent applications or, alternatively, the number of blockchain patents filed by firm i in a given fiscal year. As shown in Column (2) of Table 5, the coefficients on the main explanatory variable are insignificant, suggesting that high-ASI treated firms, relative to others, do not pursue patents more aggressively after the enactment of a law. In contrast, Column (3) displays a positive coefficient on blockchain patents (significant at the 1% level). This result shows that, compared to their counterparts, high-ASI firms significantly increase their blockchain-related innovation after the passage of a law, ostensibly in an attempt to mitigate inefficiencies arising from incomplete contracting though this technology.

Next, we estimate the economic value for a given patent application j. We calculate the (0,

[31] See details in Part A of the Internet Appendix.

+1) cumulative abnormal return (CAR), R_j, around the public announcement date of the patent application, t, using a market-adjusted model (CRSP value-weighted index). Following Kogan et al. (2017), we estimate the dollar value of a patent as the CAR multiplied by the firm's market capitalization shortly before the application disclosure, adjusted for anticipation and for the firm's total patent announcements on the same day.[32] The value is set as 0 if the firm does not file any patent in a given year. As reported in column (4) of Table 5, the coefficient on the interaction term is significantly positive, suggesting that patents filed by high-ASI firms create a higher economic value after the legislative shock. Columns (1), (3), and (4) together indicate that high-ASI firms respond proactively to pro-blockchain laws by altering their innovation activities. Despite the absence of significant changes in the overall quantity of innovation outputs, firms do appear to reallocate their resources to focus more on blockchain-related innovation and on higher-value innovation.

Apart from the results above, it is also of interest to examine changes in the generality of innovation. As discussed in Section 2, firms that are more vulnerable to hold-up problems (high-ASI firms) may be more hesitant to make investments in innovation that are specific to an existing relationship. If the usage of blockchain technology alleviates incomplete contracting problems, then relationship-specific investments should increase towards the first-best level after the enactment of a pro-blockchain law. Therefore, we expect that the passage of a pro-blockchain law reduces innovation generality more strongly for high-ASI firms.

We follow previous literature (e.g., Hall et al., 2005; Hsu et al., 2014) and calculate a patent's

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[32] Specifically, we use Equation (3) in Kogan, et al. (2017) to calculate $Economic\ value = \left(1 - \underline{\pi}\right)^{-1} \frac{1}{N_j} E[v_j | R_j] M_j$, where $\underline{\pi}$, the unconditional probability of successful patent application, is taken to be 56%; N_j is the number of patent applications a firm received on the same day; and M_j is the firm's market capitalization five trading days prior to the grant announcement date t.

generality as one minus the Herfindahl Index of the distribution of IPC codes of all the patents that cite it. The patent generality for a firm in a given year is measured as the average generality score across all patents filed by that firm in the corresponding year. As seen in Column (5) of Table 5, the coefficient on the interaction term is significantly negative, suggesting that higher-ASI firms exhibit a larger decrease in innovation generality after pro-blockchain legislation. This is consistent with our hypothesis that high ASI firms become more willing to invest in relationship-specific innovation when a pro-blockchain law mitigates the severity of hold-up problems. In untabulated robustness tests, we find similar results when we (1) exclude a firm's blockchain patents when calculating its patent generality, or (2) remove observations for which the firm filed at least one blockchain-related patent in a given year.[33] This suggests the change in innovation generality after a legislation shock is not simply being driven by an increase in blockchain-related patents.

5.2.2. Vertical Integration and Mergers and Acquisitions

Next, we turn our attention to vertical integration activity surrounding blockchain legislation. Although vertical integration can be an effective solution to contracting problems (Grossman and Hart, 1986; Hart and Moore, 1990), it is costly and can introduce other inefficiencies. When firms are able to address contractual incompleteness via technologies such as blockchains and smart contracts, vertical integration becomes less advantageous. Intuitively, this effect should be stronger for firms that are already subject to severe hold-up problems.

To test this prediction, we use vertical relatedness scores from Frésard, Hoberg, and Phillips (2020) to construct two dependent variables as firms' vertical integration outcomes: *Low Vertical Integration*, equal to one if the vertical integration score of a given firm-year observation is equal

[33] We thank an anonymous referee for suggesting these robustness tests.

to or less than the 25th percentile of the main sample, and *High Vertical Integration*, which indicates the firm-year's vertical integration score is equal to or greater than the 75th percentile.

Since mergers and acquisitions are key activities through which vertical integration can occur, we also track M&A deals surrounding legislative shocks and examine how firms' asset specificity moderates the impact of blockchain legislation on M&A activity. We obtain information on M&A deals from the Thomson Reuters SDC database. Firm-years with no M&A deals reported in the database are counted as zero. We retain deals in which both the target and the acquirer are included in the CRSP/Compustat merged database and have industry identifiers. For a target firm, if the deal is completed in the same fiscal year as the announcement, then that fiscal year-end is no longer available in the CRSP/Compustat database. Therefore, to avoid the problem of missing deal information, for a given firm-year we count the number of M&A deals announced in the subsequent year as the basic measure of M&A activity.

To capture the nature of M&A deals more precisely, we construct two groups of variables that measure the degree of vertical relatedness of an M&A deal. The first group of vertical relatedness measures follows previous work (e.g., Fan and Goyal, 2006) and utilizes the 2012 United States I-O Use table. We calculate two ratios that capture the importance of an upstream industry's (industry u) output to its downstream industry (industry d): (1) industry u's output to industry d as a portion of u's total output, and (2) industry u's output to industry d as a portion of d's total input. For a given M&A deal, we define a firm to be a potential supplier when its industry's output to its M&A counterparty's industry, measured by either one of the above two ratios,[34] is greater than or equal to the 75th percentile of the 2012 I-O table. For a given focal firm,

[34] We also alternatively require the focal firm's output to its M&A counterparty is greater than or equal to the 75th percentile when measured by *both* ratios. Untabulated tests show that our qualitative results are unchanged under this alternative approach.

we total the number of M&A deals where the focal firm is a potential supplier of its M&A counterparty to obtain a count measure, which we call *High Vertical Relatedness Deal*. For a placebo test, we also construct another count variable, *Low Vertical Relatedness Deal*, equal to the annual number of M&A deals where a focal firm is *not* a potential supplier to the M&A counterparty. When the target or the acquirer does not have I-O table information, the deal contributes to neither *High Vertical Relatedness Deal* nor *Low Vertical Relatedness Deal* (i.e., it is set to 0 for both). In untabulated robustness tests, we define potential suppliers using the 50th or 90th percentile instead of the 75th percentile, and we obtain similar results.

The results reported in Table 6 support our main prediction. Columns (1) and (2) examine a firm's vertical integration level based on its product relatedness matrix. The coefficient on the triple interaction term is significantly positive in Column (1) but significantly negative in Column (2), suggesting that high-ASI firms are more (less) likely to have low (high) vertical integration scores after legislative shocks. Column (3) is based on the occurrence of all types of M&A deals. The significantly negative coefficient on the main variable indicates that the number of M&A announcements exhibits a significantly greater decrease around blockchain statutes for higher ASI firms. In Columns (4)-(5), the dependent variable is the occurrence of high/low vertical relatedness M&A deals. The estimates in Column (4) are qualitatively similar to those for all M&A deals, suggesting that treated firms with high ASIs generally conduct fewer high vertical relatedness deals and fewer different-industry deals after legislative shocks. But the coefficient on the main variable in the placebo tests in Column (5) is small in magnitude and statistically insignificant, indicating that the results in Columns (3) and (4) are not being driven by an across-the-board reduction in all types of M&A by high-ASI firms (caused, for example, by changes in market power or other confounding factors). In untabulated robustness tests, we construct an alternative group of vertical relatedness measures based on the industry information of the target and the acquirer.[35] In line with the results in columns (4) and (5), we find the coefficient is significant and negative for different-industry deals (more likely to be vertical) but insignificant for same-industry deals. Overall, the results in Table 6 support the idea that blockchain technology is especially beneficial for high-ASI firms because it frees them from having to pursue costly vertical integration strategies.

[Insert Table 6 Here]

5.2.3. Alliances

In this section, we explore how pro-blockchain laws affect high-ASI firms' tendency to form alliances, a type of non-integrative, strategic partnership. Unlike mergers and acquisitions, alliances do not involve the combination of ownership rights under one roof and thus do not solve hold-up problems between firms. In fact, without a reliable disciplining mechanism, such deals may give rise to their own hold-up problems on account of the highly relationship-specific assets needed to form partnerships. We therefore expect that, after a legislative event, treated firms with greater asset specificity will tend to increase their participation in alliances.

To examine this prediction, we construct three measures of alliance activity that capture different aspects of alliance formation: (1) All deals, which include all types of non-M&A agreements in SDC (e.g., strategic alliances, joint ventures, R&D agreements, and marketing agreements); (2) Strategic alliances, identified by an indicator in SDC; and (3) High-tech strategic alliances, which are strategic alliance deals with at least one participant whose primary NACIS code belongs to a high-tech industry as defined following the National Science Foundation 2007

[35] When the two parties belong to different industries, the M&A activity is more likely to be vertical (Goudie, and Meeks, 1982; Davis and Duhaime, 1992). Therefore, we define different-industry M&A deals as those deals in which the target and the acquirer are not in the same SIC 4-digit industry.

NAICS codes[36].

To investigate whether a pro-blockchain environment makes alliance deals more valuable for high-ASI firms, we construct measures of the average value generated by deals filed in the same year. We first calculate the two-day, (0, +1) CAR around the public announcement of a given alliance deal using a market-adjusted model with the CRSP value-weighted index as the market. For a given firm i, the two-day CAR for a deal is scaled by the number of deals announced by the firm on the same day. We then calculate the average two-day CAR across all deals undertaken by firm i during the year. Separately, we obtain another measure of deal value by first multiplying the two-day CAR for each deal by the log-transformed market capitalization of the firm five trading days prior to the announcement. The values of a firm's deals during a given year are then averaged to yield a second measure of alliance deal values.

[Insert Table 7 here]

The results shown in Table 7 are consistent with our prediction. Relative to their out-of-state peers and low-ASI counterparts, treated firms with high ASIs exhibit an increase in all three measures of alliance deal activity in the post-legislation period. The coefficients are all significant at the 1% level and economically large. Column (1) in Panel A, for instance, shows that an increase of ASI from the 10th percentile (0.28) to the 90th percentile (0.73) translates into an increase of 0.08 in the log-transformed number of deals, which is close to half of the sample mean. Panel B presents the results of tests that examine the economic value of alliance deals. In Columns (1) and (2) of Panel B, the test is conducted at the firm level, and the dependent variable is, respectively, the average CAR and average value of all deals filed by the firm in a given year. In Columns (3) and (4), we repeat the test at the deal-firm level, where the dependent variable is the CAR or value

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[36] See https://www.nsf.gov/statistics/seind14/index.cfm/chapter-8/tt08-a.htm.

of a given deal filed by the firm. The coefficients on the main explanatory variable are significantly positive in all four specifications, suggesting that treated firms with higher ASIs gain more value from alliance deals. To ensure the larger value is not only driven by other characteristics of high-ASI firms (e.g., gaining more market power after legislative events), we conduct a third set of tests where the dependent variable is the average CARs (values) across all individual CARs (values) for participants in a deal. Columns (5) and (6) show that, after legislative shocks, the average deal value is higher when the deal has high-ASI participants.

5.2.4. Geographic Proximity of Customers

In this section, we examine the impact of pro-blockchain legislation on the geography of supplier-customer business ties. As analyzed in Section 2, being geographically close to major customers facilitates monitoring and gathering additional information flow, arguably lessening incomplete contracting problems for parties by enlarging the space of contingencies. On the other hand, restricting business ties to nearby customers limits a firm's customer pool and may entail high opportunity costs. If less-costly approaches become available for mitigating contractual incompleteness, firms can reduce their dependence on nearby customers and prioritize more valuable ties with customers outside of the local vicinity. Therefore, we predict that, after the passage of pro-blockchain laws, in-state suppliers with high ASI will tend to shift their emphasis from nearby customers to more geographically distant customers.

To test these predictions, we extract information on the major customers of sample firms from the Compustat Segment Customer dataset and construct supplier-customer pairs as described in Section 3.4. We conduct tests at both the supplier level and the pair level. In the supplier-level tests, we collapse the pair-level data to the supplier level and construct several supplier-level dependent variables that capture the geographic distance from the supplier to its customers. In

Columns (1) and (2) of Panel A, Table 8, the dependent variable is the log-transformed number of nearby customers whose headquarters is located less than 50 or 100 kilometers away from that of the focal firm. Along with fixed effects and other control variables, we also control for the yearly number of all customers (those reported in the Compustat Segment Customer dataset) associated with the focal firm. The coefficients on the main variable are significantly negative in both specifications, indicating that treated firms with high ASIs tend to have fewer major customers located nearby following legislative events. In Columns (3) and (4), when we replace the dependent variable with the fraction of a firm's customers that are within 50 or 100 kilometers, we obtain qualitatively similar results.

[Insert Table 8 Here]

Next, we examine firms' year-to-year propensities to retain nearby customers or to add remote customers. To do so, we construct two dependent variables: an indicator for whether the firm keeps at least one nearby customer from the previous year (Columns (5) and (6)) and an indicator for whether the firm adds at least one new, distant customer in a given year (Columns (7) and (8)).[37] In Columns (5) and (6), the significantly negative coefficients on the main explanatory variable indicate that, compared to their peers, high-ASI firms have a reduced tendency to keep nearby customers after being exposed to a law event. Furthermore, the results in Columns (7) and (8) show that high-ASI firms experiencing a law event are more likely to add distant customers.

We then conduct tests at the supplier-customer pair level to further examine the effects of legislation shocks and ASI on supplier-customer geographic proximity. As shown in Column (1) in Panel B, the pair distance is significantly greater when the supplier is a high-ASI firm that has experienced a legislative event. Pairs are also less likely to involve short distances (i.e., less than

[37] Due to censoring, these indicators not well-defined for years in which suppliers first begin reporting their customer information in the sample. Hence, we drop observations in these cases.

50 or 100 kilometers) when the supplier has experienced a legislative shock and has a higher ASI. Finally, echoing the results from Panel A, we find that proximate (distant) pairs are less likely to be kept (more likely to be added) when a high-ASI supplier experiences a pro-blockchain law.

5.3. Robustness

Here, we briefly outline three sets of robustness tests. First, we repeat our main tests using a different set of control firms. Specifically, we conduct tests similar to those in Tables 4 through 8, except that we use stacked regressions following the suggestion of Baker et al. (2022) in order to address potential bias in staggered diff-in-diff regressions. Details of constructing the stacked regression sample are provided in Section 4. As seen in Tables IA1-IA5 in Part B of the Internet Appendix, our main results are qualitatively similar when we use the stacked regression method.[38]

Second, to address the concern that our ASI measure might concurrently capture product similarity, we construct an alternative measure by removing any sentence that contains "product", "products", "service", or "services" from the text and recalculating the cosine similarity between pairs of business descriptions.[39] We then repeat all tests in Tables 4-8 using the alternative ASI measure. Untabulated results are both quantitatively and qualitatively similar, with the only exceptions being that the coefficient on *Post Treat* × *ASI* is not significant in column (5) of Panel B, Table 7 or column (8) of Panel A, Table 8.

Third, we conduct several additional checks to confirm that our results are not driven by the choice of the timing of law events. Specifically, we (1) follow the standard DID approach and replace $Post\ Treat_{it}$ with an indicator that is equal to one if at least one favorable blockchain

[38] When we repeat the tests in Table 7 with stacked regressions, we find all results are robust, both at the firm level and the deal-firm level. To save space, we do not tabulate deal-firm level results (columns 3-6 in Table 7) and only report firm-level results in Table IA4.
[39] We thank an anonymous referee for suggesting this alternative ASI measure.

legislation bill has been passed by year t in states where firm i operates; (2) use only the first law passed in each state (i.e., 13 laws in total); (3) use the first introduction date of a legislation bill (rather than its enactment date) as the event date; or (4) drop, in the case of treated firms, the fiscal year (or fiscal quarter when tests use quarterly data) ending immediately after the legislative event date.[40] We then repeat the tests in Tables 4 through 8. The results of these tests confirm that our main findings are robust to measuring the timing of blockchain laws in different ways.

6. Conclusion

The emergence of blockchain, a new type of decentralized ledger, is regarded by many to be a significant development that can potentially transform how modern supply chains function. To what extent can blockchain technology help alleviate the inefficiencies that arise from incomplete contracting between suppliers and customers? We attempt to answer this question with a quasi-natural experiment based on the staggered adoption of state laws that increased firms' ability to develop and use blockchains for in-state business and commerce.

We find that pro-blockchain laws can have very different effects on firm value and corporate policy, depending on whether a firm faces a high degree of ex ante exposure to incomplete contracting problems. In particular, upon the adoption of a pro-blockchain law, in-state firms with higher asset specificity exhibit relatively more positive changes to Tobin's Q and R&D and a more pronounced shift towards blockchain-related innovation instead of general innovation. Also, around a law change, treated firms with a high degree of ex ante asset specificity are more likely to eschew vertical integration strategies in favor of non-integrative deals such as strategic alliances.

[40] For M&A tests, we exclude the fiscal year ending immediately *before* the legislative event date because, for each fiscal year, we count deals that are announced in the immediately following year. We provide a more detailed explanation for this approach in Section 5.2.2.

Moreover, after a pro-blockchain law, such firms rely less on geographically proximate customers, and they become more likely to add distant customers. Taken together, these results suggest that blockchain technology can indeed help remedy constraints and inefficiencies arising from contractual incompleteness in supply-chain relationships.

In addition to providing the first systematic evidence on the effects of state blockchain laws, our paper can shed light on other issues of academic and practical interest. For instance, our text-based asset specificity measure is both firm-specific and time-varying and, as such, could be used to obtain new insights about the effects of relationship specificity and incomplete contracting within particular industries. Also, our approach of using the staggered passage of state-level blockchain legislation could potentially be applied to other important research questions concerning technological innovation, disruption, and contracting.

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Appendix A. Cleaning and Merging Different Datasets

This appendix summarizes the major steps used to clean and merge different datasets to our sample of Compustat firms. More detailed documentation of our name-matching procedures is available upon request.

A1. Name matching between Data Axle and Compustat

Data Axle (formerly known as Infogroup) is a large database that contains annual information on the physical locations of over 15 million corporate headquarters, subsidiaries, and branches in the United States. We use information from Data Axle for the time period 1997-2019. In addition to geographic locations, Data Axle also includes information on sales and the number of employees for the various corporate entities. Each data record provides identifiers for the establishment's corporation family and specifies the hierarchical position of the establishment within its firm, i.e., whether it is a parent location, a subsidiary location, or a branch location. This information makes it possible to understand whether an observation is a subsidiary, branch, or parent of another observation during the year. The information on parent-subsidiary relationships enables us to supplement our name-matching procedures (described below) with many additional correct matches between Data Axle and Compustat.

To implement our name-based matching procedure, we start with all unique firm names from Data Axle and Compustat and clean their abbreviations and suffixes, such as "INTL" and "Corp.", in two ways: (1) we expand them to the "full length" version, e.g., transforming "INTL" to "INTERNATIONAL"; and (2) we delete suffixes. In this step, we follow conservative dataset-specific rules to accommodate different norms in Data Axle and Compustat. This step generates three versions of name lists for both Compustat and Data Axle: "raw" names, "expanded" names, and “de-suffixed” names.

With abbreviations and suffixes cleaned, we next find the exact name matches between Data Axle and Compustat. Exact matches can be found by comparing the same version in both datasets, e.g., the “raw” name “STEELCASE INC” in both datasets. However, exact matches are sometimes obtained by matching different versions of a company name in the two datasets. For example, the “raw” name could be “WILLIAMS-SONOMA INC” in Compustat and “WILLIAMS-SONOMA” in Data Axle. In this case, the “de-suffixed” name in Compustat is exactly matched to the “raw” name in Data Axle.

If a parent name in Data Axle is matched to a Compustat name in this step, all its subsidiaries and branches are matched to the same Compustat name. This is useful for our matching because it handles cases where the subsidiary or branch name is completely different from the parent’s name. Similarly, if a subsidiary name in Data Axle is matched to a Compustat name on its own and not otherwise matched through a parent name, then all of its branches are matched to the same Compustat name. Finally, a branch name that is exactly matched to a Compustat name is kept only if it is not otherwise matched through a parent or subsidiary name.

Next, we implement a fuzzy matching procedure between the Compustat and Data Axle names that were not matched in the exact matching step described above. Specifically, we calculate Levenshtein distances between each unmatched Compustat name and each Data Axle parent-level name. We keep matched pairs of which the Levenshtein distance is reasonably small.[41] We then conduct a manual check of the fuzzy matching results using a firm’s industry, location, website, logo, and SEC filings where applicable. We keep the fuzzy matches that survive our manual check

[41] We keep all likely matches with Levenshtein distance no larger than 3 in parent- (or headquarter-) level fuzzy matching. Later, when performing subsidiary-level fuzzy matching, we use a threshold of 2 because the larger sample size or Cartesian product can increase noise in the matching.

procedure and again prioritize the matches first through a parent name, then through a subsidiary name, and then finally through a standalone firm name.

A2. Name matching between Data Axle and USTPO Bulk Data

To measure firms' patenting activities, we download the "Patent Application Full Text Data" and "Patent Grant Bibliographic Text Data" from the USPTO BDSS. We extract the organization assignee names as well as organization applicant names from 2013 to the present using the downloaded patent files. We then match patents to Compustat through our already-matched Data Axle names. Because Data Axle has subsidiary and branch names in addition to parent names, even if a Compustat firm files a patent through a subsidiary that has a very different name, we can still generally find the match through the subsidiary name.

There are two key challenges in this step. First, there exist a very large number of potential pairs given the hundreds of thousands of unique names in each dataset on the two sides of the matching. Second, in both Compustat and Data Axle, USPTO assignee names are less standardized compared to firm names. We employ several machine-learning approaches to overcome these two challenges.

Specifically, we first search for exact matches between Data Axle names and assignee/applicant names. We then clean up punctuation and truncate assignee/applicant names to 30 characters, which is the maximum length of firm names in Data Axle. We perform another round of exact matching based on these cleaned and truncated names.

Next, we calculate 3-gram TF-IDF string similarities between cleaned and truncated assignee/applicant names and Data Axle names. The range of TF-IDF string similarity scores is between 0 and 1. Therefore, we exclude pairs with a similarity smaller than 0.6. We then manually check the remaining pairs and exploit several variations of 3-gram TF-IDF string similarities to further improve the screening criteria for identifying valid pairs.

Finally, we train and use deep-learning models to assist with the matching. First, we employ a deep learning model based on the char2vec approach. This enables us to retrieve known correspondences between abbreviations and full names, such as the correspondence between "HELWETT-PACKARD COMPANY" and "H P INC." We also use a deep-learning model based on word2vec to retrieve known synonym name matches. As an example, we are able to infer the correspondence between "VERIZON SERVICES, CORP." and "VERIZON COMMUNICATIONS INC".[42]

A3. Identifying Supplier-Customer Pairs from Compustat Segments Customer Data

In this section, we describe the procedures used to clean the historical Compustat customer segment data, complement it with the nonhistorical Compustat customer segment data, and merge it with our main sample. First, we keep all customer names from the variable "cnms" in the Compustat customer segment data and convert them to upper case. If a name starts with the exact string "THE", we remove it. We then manually remove generic customer names like "129 CUSTOMERS", "5 ELECTRONICS STORES", and so on. Similarly, we keep all company names from the variable "comn" in Compustat and convert them to upper case. If a name starts with the exact string "THE", we remove it.

Next, we apply the Python package "string-grouper 0.1.2"[43] on the pre-processed customer and Compustat names to find possible matches between them. This package calculates the

[42] More details regarding the name matching between Data Axle and Compustat are provided in our technical notes (available upon request).
[43] New releases became available later, but the release history can be retrieved here: https://pypi.org/project/string-grouper/#history

similarity between strings based on the term frequency-inverse document frequency, a.k.a., the TF-IDF statistic. We first retain all matches with a 2-gram TF-IDF similarity greater than or equal to 0.7 or a 3-gram TF-IDF similarity greater than or equal to 0.4 for further examination. Next, we keep only the pairs satisfying either one of the following two requirements: (1) the maximum of the 2-gram and the 3-gram TF-IDF similarity is greater than or equal to 0.9, while the minimum of the 2-gram and the 3-gram TF-IDF similarity is greater than or equal to 0.65; or (2) both the 2-gram and 3-gram TF-IDF similarities are greater than or equal to 0.72, while the first letter of the customer name and the Compustat company name are the same (note that we the starting string "THE " has been removed).

The Compustat customer segment data include a "source date" variable that indicates when a supplier-customer relation was recorded. If the sales from the supplier to the customer corresponding to the source date are available, then it is also in the Compustat customer segment data. However, the source date is not the fiscal year-end date of either the customer or the supplier. Therefore, given a source date of an identified supplier-customer pair, we find the supplier and customer's fiscal year-end dates that precede the source date but are within three years of it. We also require the customer's fiscal year-end date to be within a one-year window before and after the supplier's fiscal year-end date. Finally, for a supplier-customer pair on a given source date, we keep the latest fiscal year-end dates for the supplier and the customer.

Appendix B. Variable Definitions

The table below provides detailed definition for key (raw) variables.

Variable	Definition
Asset Specificity Index (ASI)	One minus the average similarity score between a focal firm and its five most similar firms. Similarity between two firms is calculated as the cosine similarity between their 10-K filing "Item 1" sections for the same year.
Tobin's Q	Calculated as the ratio of the market value of equity, plus total assets, minus the book value of common equity, to total assets. Compustat: (PRCC_F × CSHO + AT – CEQ) / AT
Tobin's Q, Alternative Measure	An alternative measure of Tobin's Q, calculated as the ratio of the book value of debt, plus the market value of equity, minus the firm's current assets, to the book value of property, plant, and equipment. Compustat: (DLTT + DLC + PRCC_F × CSHO – ACT) / PPEGT. Firms with PPEGT less than $5 million are excluded.
R&D Intensity	R&D expenditures divided by sales
All Patents	The total number of patent applications filed by a firm in a given year
Blockchain Patents	The number of patent applications filed by a firm in a given year that are specifically related to blockchain
Patent Value	The average value of patent applications filed by a firm during the year. The value of a patent application is calculated using the method of Kogan et al. (2017).
Patent Generality	The generality of a patent is measured as one minus the Herfindahl Index of three-digit IPC codes across all other patents that cite it. A firm's innovation generality in a given year is the average patent generality across all patents that the firm files during the year.
High (Low) Vertical Integration	An indicator equals one if a firm's vertical integration score in a given year is greater than or equal to the 75th percentile (less than or equal to the 25th percentile) in the overall sample. The vertical integration score is from Frésard, Hoberg, and Phillips (2020).
M&A Deals – All	The total number of M&A deals that a firm announces in a given year.
M&A Deals – High Vertical Relatedness	The number of M&A deals where the focal firm and counterparty of the deal have a high likelihood of a potential supplier-customer relationship with the focal firm as the supplier. Potential supplier-customer relationships are defined based on data from the 2012 I-O table.
Alliance Deals, All	The total number of alliance deals announced by a firm in a given year.
Alliance Deals, Strategic	The number of alliance deals announced by a firm in a given year that are identified as strategic alliances by the Thomson Reuters SDC database.

Alliance Deals, HighTech Strategic	The total number of strategic alliances announced during the year by a firm for which at least one partner's primary NACIS code corresponds to a high-tech industry. High-tech industries are as defined according to the National Science Foundation (https://www.nsf.gov/statistics/seind14/index.cfm/chapter-8/tt08-a.htm).
Alliance Deals Avg. CARs (%)	The average of the (0, +1) announcement CARs of all alliance deals announced by a firm in a given year, multiplied by 100. Each announcement CAR is scaled by the number of alliance deals announced by the firm on the event day.
Alliance Deals Avg. Value	The average of value of all alliance deals announced by a firm in a given year, where deal value is calculated as the product of the two-day, (0, +1) announcement CAR and the firm's log-transformed market capitalization 5 trading days prior to the announcement.
# of Nearby Customers ≤ 50km	The number of nearby customers a supplier has in a given year, where nearby customers are defined as those headquartered within 50 kilometers.
# of Nearby Customers ≤ 100km	The number of nearby customers a supplier has in a given year, where nearby customers are defined as those headquartered within 100 kilometers.
Supplier-Customer Pair Distance	The distance between a supplier's headquarters and a customer's headquarters, in kilometers.
Size	Compustat variable AT (total assets)
ROA	Compustat variable NI divided by Compustat variable AT, i.e., net income over total assets
Cash	Cash and short-term investments scaled by total assets, measured by Compustat variables as CHE/AT.
Sales	Sales scaled by total assets, measured with Compustat variables as SALE/AT
HHI	The sum of the squared market share (market share = firm sales/industry sales) of all individual firms in an industry., where the industry is defined at the NAICS 5-digit level.
Industry Intangibles	Weighted-average intangible assets (Compustat variable INTAN) across firms in the industry, where industry is defined at the NAICS 5-digit level. Missing values are replaced with zeros. A firm's weight is calculated as its total assets divided by the aggregated total assets of all firms in the same industry.
Industry R&D	Weighted-average R&D expense (Compustat variable XRD) across firms in the industry, where industry is defined at the NAICS 5-digit level. Missing values are replaced with zeroes. A firm's weight is calculated as total assets divided by the aggregated total assets of all firms in the same industry.

Figure 1. Effect of Pro-Blockchain Laws and Asset Specificity (ASI) on Tobin's Q

The graph below plots the coefficients of interest and 95% confidence intervals from a regression of Tobin's Q on yearly triple-interaction terms using a stacked firm-year-legislation sample. The event year, which serves as the baseline year in the regression, is the latest fiscal year ending prior to the law enactment date. Only observations from three years before to three years after the baseline year are included in the regression. *Tobin's Q* is calculated from Compustat items as (PRCC_F × CSHO + AT – CEQ) / AT. For a given firm i in year t, the indicator $I_{ijt\_m}(t\ is\ m\ years\ before\ event)$ is equal to one for the m^{th} year before the event year corresponding to legislation j; otherwise, it is zero. Similarly, for a given firm i in year t, the indicator $I_{ijt\_n}(t\ is\ n\ years\ after\ event)$ is equal to one for the n^{th} year after the event year corresponding to legislation j; otherwise it is zero. We plot the estimated coefficients on interaction terms between these indicators and $High\ ASI$, which is an indicator for firms with an asset specificity index (ASI) equal to or above the median value in the overall test sample. For a given firm i, if it is impacted by legislation j, the dummy $Treat_{ij}$ is equal to 1; if it is in the control sample for legislation j, the dummy $Treat_{ij}$ is equal to 0. Control variables Z_{it} include *Size*, measured by total assets; *ROA*, net income over total assets; *Cash,* cash and short-term investments scaled by total assets; *Sales*, net sales scaled by total assets; *Industry Intangibles,* the weighted average intangible assets across firms in the industry; and *Industry R&D*, the weighted average R&D expenses across firms in the industry. (Weights used in constructing *Industry Intangibles* and *Industry R&D* are equal to a firm's total assets divided by the aggregated total assets of all firms in the same industry.) Missing values of intangible assets and R&D are replaced with zero when calculating *Industry Intangibles* and *Industry R&D*. *HHI* is the sum of squared revenue market shares of all the individual firms in an industry. *Industry Intangibles, Industry R&D, and HHI* are calculated at the NAICS 5-digit level. *Tobin's Q*, *Size*, *Industry Intangibles*, and *Industry R&D* are log-transformed in the regression. The regression includes firm × law fixed effects and year × law fixed effects. Robust standard errors are clustered at the firm × law level.

$$
\begin{aligned}
Tobin's\ Q_{ijt} = \alpha &+ \sum_{m=1}^{3} \beta_m I_{ijt\_m}(t\ is\ m\ years\ before\ event) \times Treat_{ij} \times High\ ASI_{it} \\
&+ \sum_{n=1}^{3} \beta_n I_{ijt\_n}(t\ is\ n\ years\ after\ event) \times Treat_{ij} \times High\ ASI_{it} \\
&+ \sum_{m=1}^{3} \zeta_m I_{ijt\_m}(t\ is\ m\ years\ before\ event) \times Treat_{ij} \\
&+ \sum_{n=1}^{3} \zeta_n I_{ijt\_n}(t\ is\ n\ years\ after\ event) \times Treat_{ij} + \delta_2 Treat_{ij} \times High\ ASI_{it} \\
&+ \delta_3 High\ ASI_{it} + \gamma Z_{it} + \eta_{ij} + \xi_{jt} + \epsilon_{ijt}
\end{aligned}
$$

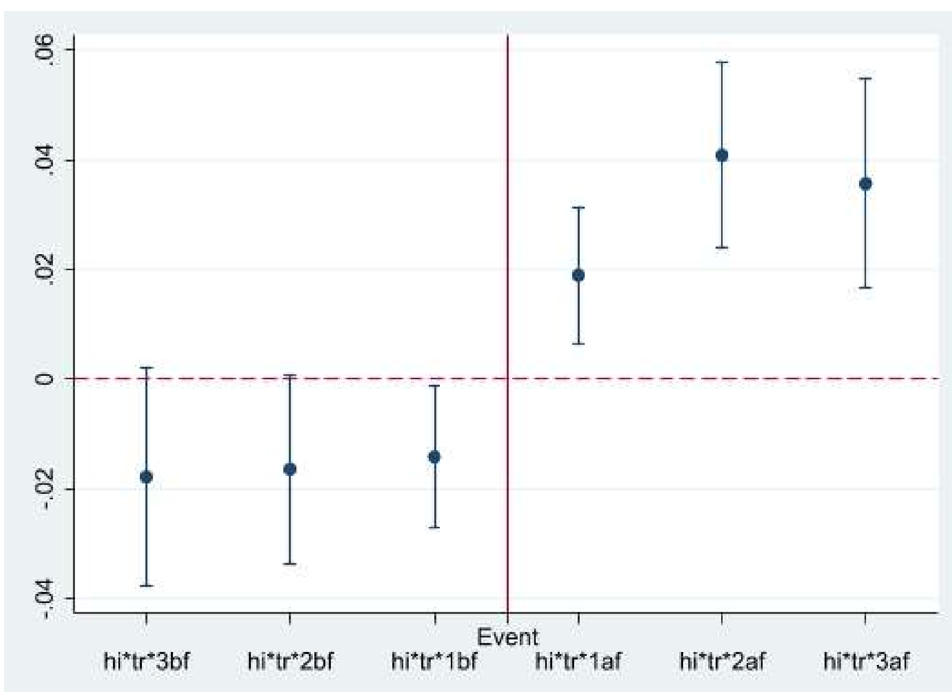

Table 1. Enacted State Laws Favorable to Blockchain

This table summarizes state laws favorable to the use of blockchain in private-sector business and commerce. For each law, the table shows the enacting state, legislation bill number, date of introduction (first reading in the state legislature), date of enactment into law, and a brief description of core provisions.

State	Bill No.	Introduced	Enacted	Core Provisions
AR	HB 1944	27-Mar-19	16-Apr-19	Provides that a signature or contract on blockchain is electronic form; provides that a smart contract shall be a commercial contract
AZ	HB 2417	7-Feb-17	29-Mar-17	Recognizes smart contracts in commerce (certain exceptions for cases where terms of transaction expressly transfer ownership or use of information secured by blockchain technology)
AZ	HB 2602	6-Feb-18	12-Apr-18	Provides that running a blockchain node in a residence is a state concern; prohibits cities, towns, or counties from impeding a person running a node on blockchain technology in a residence
IL	HB 3575	15-Feb-19	23-Aug-19	Creates the Blockchain Technology Act; provides for permitted uses and limitations to blockchain technology; prohibits local governments from restricting blockchain use
ND	HB 1045	3-Jan-19	24-Apr-19	Legitimizes blockchain, smart contracts, and electronic signatures in commerce
NV	SB 398	20-Mar-17	05-Jun-17	Recognizes blockchain as a type of electronic record for UETA; prohibits local government from taxing or restricting use of a blockchain
NV	SB 162	14-Feb-19	07-Jun-19	Affirms blockchain as a type of electronic record for the UETA; provides that user of a public blockchain does not relinquish any right of ownership; prohibits local government from taxing or imposing restrictions upon use of a public blockchain
NV	SB 163	14-Feb-19	07-Jun-19	Revises the definition of electronic transmission for certain businesses to include blockchain; allows certain business entities to store records and carry out their duties with blockchain

Continued on next page

Table 1, continued

OH	SB 220	17-Oct-17	03-Aug-18	Allows transactions recorded by blockchain technology under the Uniform Electronic Transactions Act (UETA)
OK	SB 700	04-Feb-19	25-Apr-19	Relates blockchain to the definition of electronic records and the UETA
SD	HB 1196	30-Jan-19	7-Mar-19	Revises definitions of electronic transmission and contracting to include blockchain
TN	HB 1507 /SB 1662	11-Jan-18	22-Mar-18	Recognizes the legal authority to use blockchain technology and smart contracts in conducting electronic transactions; protects ownership rights with respect to information secured by blockchain
UT	SB 213	26-Feb-19	26-Mar-19	Defines and clarifies terms related to blockchain technology. Exempts a person who exchanges, sells certain blockchain products from the Money Transmitter Act
VT	HB 868	15-Mar-16	02-Jun-16	Creates statutory presumptions of authenticity for records using blockchain technology
WA	SB 5638	25-Jan-19	26-Apr-19	Recognizes the validity of distributed ledger technology. Affirms that electronic records may not be denied legal effect or enforceability solely because they are related to DLT (distributed ledger technology)
WY	HB 70	13-Feb-18	12-Mar-18	Affirms that a person who develops, sells, or exchanges an open blockchain token is not subject to specified securities and money transmission laws

Table 2. Summary Statistics: Asset Specificity Index (ASI)

This table presents summary statistics at the business sector level for the constructed asset specificity index (ASI) over 2011-2021. Firm-year observations from CRSP/Compustat are included. *ASI* is one minus the average similarity score between a focal firm and its five most similar firms. The textual similarity between two firms is the cosine similarity between their "Item 1" sections in their 10-K filings for the same year. Details are provided in Section 3.3. Sectors are defined based on 2-digit NAICS codes following the United States Census Bureau 2017 NAICS table: https://www.census.gov/naics/?58967?yearbck=2017.

NAICS	Sector	N	Mean	Std. Dev.
	All	34,243	0.531	0.169
11	Agriculture, Forestry, Fishing and Hunting	98	0.626	0.171
54	Professional, Scientific, and Technical Services	1,290	0.603	0.117
42	Wholesale Trade	1,142	0.592	0.145
56	Administrative and Support and Waste Management and Remediation Services	701	0.588	0.142
51	Information	3,733	0.578	0.148
31-33	Manufacturing	14,873	0.578	0.14
71	Arts, Entertainment, and Recreation	257	0.530	0.186
23	Construction	567	0.519	0.175
81	Other Services (except Public Administration)	90	0.514	0.185
44-45	Retail Trade	1,661	0.513	0.143
22	Utilities	650	0.512	0.12
53	Real Estate and Rental and Leasing	1,510	0.501	0.164
62	Health Care and Social Assistance	611	0.461	0.157
48-49	Transportation and Warehousing	939	0.402	0.144
52	Finance and Insurance	2,765	0.384	0.191
72	Accommodation and Food Services	726	0.379	0.161
21	Mining, Quarrying, and Oil and Gas Extraction	1,753	0.368	0.158
61	Educational Services	187	0.362	0.202
	Other	690	0.535	0.175

Table 3. Summary Statistics

This table reports summary statistics for annual firm characteristics for the CRSP/Compustat merged sample over 2011-2021. Firm-year observations are included when Tobin's Q and all explanatory variables are non-missing. *Tobin's Q* is calculated from Compustat items as (PRCC_F × CSHO + AT – CEQ) / AT. *Tobin's Q, Alt* is calculated from Compustat items as (DLTT + DLC + PRCC_F × CSHO – ACT) / PPEGT. We exclude firms whose PPEGT is less than 5 million when constructing *Tobin's Q, Alt*. *R&D Intensity* is defined as R&D expenditures divided by sales. Missing values of R&D are treated as missing. Data on patent applications and citations are obtained from the USPTO database. Firm years with no patent application record in the USPTO database are counted as zero. *All Patents* is the total number of patent applications filed by a firm in a given year. *Blockchain Patents* is the number of blockchain patent applications filed by a firm in a given year. Blockchain patents are identified as described in Section 3.4. *Patent Value* is the average value generated by all patent applications filed by the firm in a given year. The value is set as 0 if the firm does not file any patents in a given year. The value of a given patent application is calculated following Kogan et al. (2017) (details are given in Section 5.2.1). *Patent Generality* is the average level of patent generality across all patents filed by a firm in a given year, where the generality of a patent is measured as one minus the Herfindahl Index of the international patent classification (IPC) codes across all other patents that cite it. *High (Low) Vertical Integration* is an indicator equal to one if a firm's vertical integration score in a given year is greater than or equal to the 75th percentile (less than or equal to the 25th percentile) of the overall sample. The vertical integration score is from Frésard, Hoberg, and Phillips (2020) (downloaded from the Frésard-Hoberg-Phillips Vertical Relatedness Data Library in April 2023). Data on M&A deals and alliances are obtained from Thomson Reuters SDC database and aggregated at the yearly level. Firm years with no M&A or alliances reported in the SDC Platinum database are counted as zero. *M&A Deal - All* is the total number of U.S. public M&A deals announced by a firm in a given year. *M&A Deals – High Vertical Relatedness* is the number of M&A deals announced by a firm in a given year where the focal firm and counterparty of the deal have a high potential of a supplier-customer relationship and the focal firm is the potential supplier. Supplier-customer relationship potential is defined based on the 2012 I-O table (details are provided in Section 5.2.2). *Alliance Deals –All* is the total number of alliance deals announced by a firm in a given year. *Alliance Deals –Strategic* is the number of alliance deals announced by a firm in a given year that are identified as strategic alliances by the SDC database. *Alliance Deals –HighTech Strategic* is the number of strategic alliance deals for which at least one deal partner's primary NACIS code belongs to a high-tech industry. High-tech industries are as defined by the National Science Foundation based on 2007 NAICS codes (see https://www.nsf.gov/statistics/seind14/index.cfm/chapter-8/tt08-a.htm). *Avg. CAR* is the average of the (0, +1) announcement CARs of all alliance deals announced by a firm in a given year, multiplied by 100. Announcement CARs are scaled by the number of deals announced by a firm on the same event day. *Avg. Value* is the average of value of all alliance deals announced by a firm in a given year, where deal value is calculated as the product of the 2-day announcement CAR and the firm's log-transformed market capitalization 5 trading days prior to the announcement. *# of Nearby Cust.* is the number of nearby customers a firm has in a given year, where nearby customers are defined as those headquartered within 50 (100) kilometers. *Pair Distance* is the distance between a firm's headquarters and its customer's headquarters (in kilometers) at the pair-year level. *Size* is total assets. *ROA* is net income divided by total assets. *Cash* is cash and short-term investments scaled by total assets. *Sales* is net sales scaled by total assets. *Industry Intangibles* is the weighted average of firms' intangible assets in the industry. *Industry R&D* is the weighted average of firms' R&D expenses in the industry. (Weights used in constructing these two variables are equal to a firm's total assets divided by the aggregated total assets of all firms in the same industry.) Missing values of intangible assets and R&D are replaced with zero when calculating *Industry Intangibles* and *Industry R&D*. *HHI* is the sum of the squared market share (market share = firm sales/industry sales) of all the individual firms in an industry. *Industry Intangibles, Industry R&D, and HHI* are calculated at the NAICS 5-digit level. All continuous variables are winsorized at the 1% and 99% level. *Tobin's Q*, *Tobin's Q, Alt*, *R&D Intensity*, *All Patents*, *Blockchain Patents*, *Patent Value*, *Size*, *Industry Intangibles*, and *Industry R&D* are log-transformed.

Table 3, continued

	N	Mean	Std. Dev.	Min	Median	Max
Dependent Variables						
Tobin's Q	34,183	1.065	0.425	0.473	0.943	2.614
Tobin's Q, Alt.	26,957	1.453	1.139	-0.786	1.197	4.768
R&D Intensity	20,285	0.299	0.751	0	0.049	4.496
All Patents	34,243	18.171	181.170	0	0	10,585
Blockchain Patents	34,243	0.045	1.852	0	0	222
Patent Value	34,243	3.451	4.612	0	0	12.599
Patent Generality	34,243	0.082	0.190	0	0	0.75
Low Vertical Integration	34,176	0.216	0.412	0	0	1
High Vertical Integration	34,176	0.274	0.446	0	0	1
M&A Deals – All	34,243	0.032	0.182	0	0	4
M&A Deals – High Vertical Relatedness	34,243	0.021	0.147	0	0	3
Alliance Deals: All	34,243	0.341	1.421	0	0	82
Alliance Deals: Strategic	34,243	0.264	1.252	0	0	75
Alliance Deals: HighTech Strategic	34,243	0.179	1.095	0	0	75
Alliance Deals: Avg. CAR (%)	5,433	0.828	4.850	-11.335	0.158	26.111
Alliance Deals: Avg. Value	5,433	0.102	0.619	-1.561	0.026	3.154
# of Nearby Customers, ≤ 50km	7,599	0.249	0.642	0	0	7
# of Nearby Customers, ≤ 100km	7,599	0.281	0.674	0	0	7
Pair HQ Distance	15,701	1,511	1,278	0	1,184	4,318
Controls						
Size	34,243	6.725	2.079	2.086	6.782	11.695
ROA	34,243	-0.049	0.266	-1.671	0.021	0.344
Cash	34,243	0.210	0.237	0.0005	0.115	0.971
Sales	34,243	0.850	0.733	0.00001	0.676	3.672
HHI	34,243	0.239	0.236	0.025	0.159	1
Industry Intangibles	34,243	8.122	2.037	0.815	8.463	10.997
Industry R&D	34,243	4.019	3.442	0	4.025	9.178

Table 4. Blockchain Legislation and Firm Value

This table reports results of regressions that explain firm value after the enactment of state legislation favorable to the in-state use of blockchain technology in business and commerce. The sample consists of firm-year observations of all CRSP/Compustat firms from 2011 to 2021. In Column (1), the dependent variable, *Tobin's Q*, is calculated from Compustat items as (PRCC_F × CSHO + AT – CEQ) / AT. In Column (2), the dependent variable *Tobin's Q Alt.* is calculated from Compustat items as (DLTT + DLC + PRCC_F × CSHO – ACT) / PPEGT. Columns (3) and (4) are at the quarterly level, and the dependent variables correspond to the Tobin's Q measures in Columns (1) and (2), respectively. In Columns (2) and (4), observations are dropped if the annual PPEGT is less than \$5 million. In Column (4), missing annual values of PPEGT are replaced with PPEGTQ in the fourth quarter of the same fiscal year, if available. The main explanatory variable, *Post Treat × ASI,* is the interaction of *Post Treat* and *ASI. Post Treat* is a binary variable equal to one if a given fiscal year end of an in-state firm is within the 3-year window following the passage of a blockchain legislation event date, and 0 otherwise. *ASI* is one minus the average textual similarity score between a focal firm and its five most similar firms, where textual similarity between two firms is the cosine similarity between firms' "Item 1" sections in their 10-K filings for the same year. (Details of the construction of the ASI score are provided in Section 3.3.) *Treat × ASI* is the interaction of *Treat* and *ASI. Treat* indicates firms that experience at least one legislation event during the sample period. *Size* is total assets. *ROA* is net income over total assets. *Cash* is the cash and short-term investments scaled by total assets. *Sales* is net sales scaled by total assets. *Industry Intangibles* is the weighted average of firms' intangible assets in the industry. *Industry R&D* is the weighted average of firms' R&D expenses in the industry. (Weights used in constructing these two variables are equal to a firm's total assets divided by the aggregated total assets of all firms in the same industry.) Missing values of intangible assets and R&D are replaced with zero when calculating *Industry Intangibles* and *Industry R&D*. *Industry Intangibles, Industry R&D, and HHI* are all at the NAICS 5-digit level. Firm and industry controls in Columns (1) and (2) are at the annual level, while controls in Columns (3) and (4) are at the quarterly level. All continuous variables except for *ASI* are winsorized at the 1% and 99% levels. *Tobin's Q*, *Tobin's Q, Alt*, *Tobin's Q, Quarterly, Tobin's Q Alt., Quarterly, Size*, *Industry Intangibles*, and *Industry R&D* are log-transformed. All regressions include firm fixed effects and year (or quarter) fixed effects. Robust standard errors, clustered at the firm level, are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 4, continued

	Tobin's Q (1)	*Tobin's Q Alt.* (2)	*Tobin's Q, Quarterly* (3)	*Tobin's Q Alt., Quarterly* (4)
Post Treat × ASI	0.154***	0.267***	0.140***	0.283***
	(0.03)	(0.07)	(0.03)	(0.07)
Post Treat	-0.078***	-0.140***	-0.066***	-0.115***
	(0.02)	(0.04)	(0.02)	(0.04)
Treat × ASI	-0.101	-0.152	-0.042	-0.081
	(0.07)	(0.21)	(0.07)	(0.20)
ASI	0.089	0.145	0.027	-0.006
	(0.06)	(0.17)	(0.06)	(0.17)
Size	-0.058***	0.114***	-0.064***	0.129***
	(0.01)	(0.02)	(0.01)	(0.02)
ROA	0.026	0.660***	-0.086**	1.083***
	(0.02)	(0.05)	(0.04)	(0.09)
Cash	0.339***	0.621***	0.293***	0.728***
	(0.03)	(0.07)	(0.02)	(0.07)
Sales	0.144***	-0.052**	0.587***	0.196***
	(0.01)	(0.03)	(0.03)	(0.07)
HHI	-0.041**	-0.008	-0.152**	-0.152
	(0.02)	(0.05)	(0.07)	(0.18)
Industry Intangibles	0.012***	0.031***	0.013***	0.034***
	(0.00)	(0.01)	(0.00)	(0.01)
Industry R&D	-0.000	-0.002	0.002	-0.003
	(0.00)	(0.01)	(0.00)	(0.01)
Firm FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	No	No
Quarter FEs	No	No	Yes	Yes
Observations	33,322	26,463	138,458	72,970
Adj. R-squared	0.766	0.845	0.806	0.866

Table 5. Blockchain Legislation and Innovation

This table reports estimates from regressions that explain firms' innovation activity following the passage of legislation favorable to the in-state use of blockchain technology in business and commerce. The sample consists of firm-year observations of all CRSP/Compustat firms from 2011 to 2021. *R&D Intensity* is is defined as R&D expenditures over sales. Missing values of R&D are treated as missing. *All Patents* is the total number of patent applications that a firm files in a given year. *Blockchain Patents* is the number of blockchain patent applications that a firm files in a given year. Blockchain patents are identified as described in Section 3.4. *Patent Value* is the average value of all patent applications filed in a given year (it is set to 0 if the firm does not file any patents during the year). The value of a patent application is calculated following the method of Kogan et al. (2017) as described in Section 5.2.1. *Patent Generality* is the average of patent generality across all patents filed by the firm in a given year, while the generality of a patent is measured as one minus the Herfindahl Index of the international patent classification (IPC) codes across all other patents that cite it (the value is set to 0 if the firm does not file any patents during the year). Data on patent applications and citations are obtained from the USPTO database. Firm years with no patent application record in the USPTO database are counted as zero. The main explanatory variables and other control variables are as described in Table 4. The *All Patents* variable and all continuous variables (except for *ASI*) are winsorized at the 1% and 99% levels. *R&D Intensity*, *All Patents*, *Blockchain Patents*, *Patent Value*, *Size*, *Industry Intangibles*, and *Industry R&D* are log-transformed. All regressions include firm and year fixed effects. Robust standard errors, clustered at the firm level, are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 5, continued

	R&D Intensity (1)	*All Patents* (2)	*Blockchain Patents* (3)	*Patent Value* (4)	*Patent Generality* (5)
Post Treat × ASI	0.079**	-0.081	0.082***	0.800**	-0.151***
	(0.03)	(0.07)	(0.03)	(0.36)	(0.02)
Post Treat	-0.020	0.045	-0.025**	-0.377*	0.070***
	(0.02)	(0.04)	(0.01)	(0.21)	(0.01)
Treat × ASI	0.184	-0.062	0.039	-0.833	0.082**
	(0.14)	(0.15)	(0.03)	(0.72)	(0.04)
ASI	-0.189	0.137	-0.001	0.171	-0.034
	(0.13)	(0.09)	(0.01)	(0.45)	(0.02)
Size	-0.026*	0.137***	-0.001	0.632***	-0.006*
	(0.01)	(0.01)	(0.00)	(0.06)	(0.00)
ROA	-0.489***	-0.115***	0.001	-0.380***	0.002
	(0.05)	(0.02)	(0.00)	(0.10)	(0.01)
Cash	0.362***	-0.012	-0.012*	-0.002	0.043***
	(0.06)	(0.05)	(0.01)	(0.20)	(0.01)
Sales	-0.275***	-0.010	0.000	0.072	-0.013***
	(0.02)	(0.01)	(0.00)	(0.07)	(0.00)
HHI	0.013	0.018	-0.000	0.089	-0.001
	(0.02)	(0.05)	(0.01)	(0.22)	(0.01)
Industry Intangibles	0.003	-0.002	0.000	0.013	-0.002
	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
Industry R&D	0.001	0.017***	0.001*	0.056**	0.001
	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
Firm FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	19,833	33,381	33,381	33,381	33,381
Adj. R-squared	0.813	0.880	0.380	0.720	0.485

Table 6. Blockchain Legislation and Vertical Integration Activity

This table shows results from regressions that explain firms' vertical integration activity following the passage of legislation favorable to the in-state use of blockchain technology in business and commerce. The sample consists of firm-year observations of CRSP/Compustat firms from 2011 to 2021. *High (Low) Vertical Integration* is an indicator equal to 1 if a firm's vertical integration score in a given year is greater than or equal to the 75th percentile (less than or equal to the 25th percentile) of the overall sample. The vertical integration score is drawn from Frésard, Hoberg, and Phillips (2020) (downloaded from the Frésard-Hoberg-Phillips Vertical Relatedness Data Library as of April 2023). *All M&A Deals* is the total number of M&A deals a firm announces in a given year. An M&A deal is counted when both the target firm and the acquirer are included in the CRSP/Compustat merged data. *High (Low) Vertical Relatedness Deals* is the number of M&A deals for which the focal firm and counterparty of the deal have a high-level (low-level) supplier-customer relationship and the focal firm is the potential supplier. Supplier-customer relationships are defined based on the 2012 I-O table (details provided in Section 5.2.2). M&A deals are measured as of the year following a given fiscal year end. Data on M&A deals are obtained from Thomson Reuters SDC database and aggregated at the yearly level. Firm-years with no reported M&A in the SDC Platinum database are counted as zero. The main explanatory variable and other control variable are defined as described in Table 4. *Size*, *Industry Intangibles*, and *Industry R&D* are log-transformed. All continuous variables except for *ASI* are winsorized at the 1% and 99% levels. All regressions include firm and year fixed effects. Robust standard errors, clustered at the firm level, are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	Low Vertical Integration	*High Vertical Integration*	*All M&A Deals*	*High Vertical Relatedness Deals*	*Low Vertical Relatedness Deals*
	(1)	(2)	(3)	(4)	(5)
Post Treat × ASI	0.078**	-0.098***	-0.043**	-0.031**	-0.009
	(0.03)	(0.04)	(0.02)	(0.02)	(0.01)
Post Treat	-0.057***	0.058***	0.007	0.006	-0.000
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Treat × ASI	-0.012	-0.141*	0.014	0.037	-0.022
	(0.09)	(0.07)	(0.04)	(0.03)	(0.03)
ASI	0.014	0.079*	-0.055**	-0.045**	-0.008
	(0.07)	(0.04)	(0.03)	(0.02)	(0.01)
Size	-0.013**	0.022***	-0.009***	-0.006**	-0.003**
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
ROA	-0.009	-0.011	0.012**	0.012***	0.003
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Cash	0.017	-0.022	0.027**	0.013	0.013**
	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)
Sales	-0.005	0.007	0.010***	0.004	0.006**
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)

Continued on next page

Table 6, continued

HHI	-0.021	0.028	0.003	0.004	-0.002
	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)
Industry Intangibles	0.001	-0.001	-0.002	-0.002**	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Industry R&D	-0.000	0.002	0.002*	0.001**	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	33,311	33,311	33,381	33,381	33,381
Adj. R-squared	0.681	0.760	0.103	0.108	0.082

Table 7. Blockchain Legislation and Alliances

This table presents results of regressions that explain firms' formation of alliances following the passage of legislation favorable to the in-state use of blockchain technology in business and commerce. Data on alliances are obtained from the Thomson Reuters SDC database. We include deals for which at least one deal participant-year observation is covered in the CRSP/Compustat merged database. In Panel A, the sample consists of firm-year observations of all CRSP/Compustat firms from 2011 to 2021. *All Alliance Deals* is the total number of alliance deals announced in a given year. *Strategic Alliance Deals* is the number of alliance deals announced in a given year that are identified as strategic alliances by the SDC database. *High Tech Strategic Alliance Deals* is the number of strategic alliance deals where at least one partner firm's primary NACIS code belongs to a high-tech industry. High-tech industries are as defined by the National Science Foundation (based on 2007 NAICS codes) (https://www.nsf.gov/statistics/seind14/index.cfm/chapter-8/tt08-a.htm). In Panel A, firm-years with no alliance deal reported in the SDC Platinum database are counted as zero. Panel B focuses on the value of alliance deals. In Columns (1) and (2), the sample of firm-years is restricted to firms that file at least one alliance deal in a given year. *Avg. CAR* is the average of the (0, +1) announcement CARs of all alliance deals announced by a firm in a given year, multiplied by 100. Each announcement CAR is scaled by the number of deals announced by the firm on the same event day. *Avg. Value* is the average of value of all alliance deals announced by a firm in a given year, where deal value is calculated as the product of the 2-day announcement CAR and the firm's log-transformed market capitalization 5 trading days prior to the announcement. In Columns (3) and (4), the data are at the deal-firm level. *CAR* is the (0, +1) CAR of a given firm surrounding the announcement of the deal, scaled by multiplying the original value by 100. *Value* is the deal value of a given deal, calculated as *CAR* multiplied by the log-transformed market capitalization of the firm five trading days prior to the announcement. In Columns (5) and (6), the data are at the deal-firm level. *Avg. CAR* is the aggregation of (0, +1) CARs across all participants in a deal, divided by the number of participants and scaled by multiplying the original value by 100. *Avg. Value* is the aggregated deal value for all participants in a deal, divided by the number of participants. The main explanatory variable and other control variables are as described in Table 4. All continuous variables except for *ASI* are winsorized at the 1% and 99% levels. *All Alliance Deals*, *Strategic Alliance Deals*, *High Tech Strategic Alliance Deals*, *Size*, *Industry Intangibles*, and *Industry R&D* are log-transformed. All regressions include firm and year fixed effects. Robust standard errors, clustered at the firm level, are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 7, continued

Panel A. Number of Alliance Deals			
	All Alliance Deals	*Strategic Alliance Deals*	*High-Tech Strategic Alliance Deals*
	(1)	(2)	(3)
Post Treat × ASI	0.172***	0.146***	0.148***
	(0.04)	(0.04)	(0.03)
Post Treat	-0.067***	-0.033	-0.076***
	(0.02)	(0.02)	(0.01)
Treat × ASI	-0.099	-0.026	-0.059
	(0.08)	(0.07)	(0.06)
ASI	0.042	0.018	0.007
	(0.05)	(0.04)	(0.04)
Size	0.054***	0.035***	0.029***
	(0.01)	(0.01)	(0.00)
ROA	-0.031**	-0.020*	-0.008
	(0.01)	(0.01)	(0.01)
Cash	-0.006	-0.001	-0.019
	(0.02)	(0.02)	(0.02)
Sales	-0.004	-0.007	-0.004
	(0.01)	(0.01)	(0.01)
HHI	0.015	0.004	0.009
	(0.02)	(0.02)	(0.02)
Industry Intangibles	-0.001	-0.005*	-0.003*
	(0.00)	(0.00)	(0.00)
Industry R&D	0.010***	0.010***	0.008***
	(0.00)	(0.00)	(0.00)
Firm FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Observations	33,381	33,381	33,381
Adj. R-squared	0.386	0.355	0.380

Continued on next page

Table 7, continued

Panel B. Value of Alliance Deals						
	Firm Level		Deal-Firm Level		Deal-Firm Level	
	Avg. CAR	*Avg. Value*	*CAR*	*Value*	*Avg. CAR*	*Avg. Value*
	(1)	(2)	(3)	(4)	(5)	(6)
Post Treat × ASI	2.829***	0.394***	2.266***	0.323***	1.821**	0.265**
	(0.97)	(0.13)	(0.77)	(0.11)	(0.74)	(0.11)
Post Treat	-1.957***	-0.264***	-1.456***	-0.201***	-1.110**	-0.157**
	(0.64)	(0.09)	(0.52)	(0.07)	(0.49)	(0.07)
Treat × ASI	-0.550	-0.033	-2.497	-0.376	-1.424	-0.228
	(4.08)	(0.52)	(2.88)	(0.38)	(2.67)	(0.36)
ASI	2.377	0.265	2.201	0.296	1.068	0.143
	(3.80)	(0.48)	(2.66)	(0.34)	(2.41)	(0.31)
Size	-0.496	-0.063	-0.504**	-0.071**	-0.377*	-0.055*
	(0.31)	(0.04)	(0.22)	(0.03)	(0.21)	(0.03)
ROA	1.478	0.203*	0.951	0.136	0.716	0.108
	(0.93)	(0.11)	(0.79)	(0.09)	(0.71)	(0.09)
Cash	1.192	0.142	0.090	0.006	-0.434	-0.053
	(1.38)	(0.17)	(0.96)	(0.12)	(0.89)	(0.11)
Sales	0.417	0.038	0.268	0.015	0.460	0.044
	(0.57)	(0.07)	(0.49)	(0.06)	(0.42)	(0.05)
HHI	0.187	0.010	-0.305	-0.043	-0.580	-0.080
	(0.99)	(0.13)	(0.70)	(0.09)	(0.66)	(0.09)
Industry Intangibles	0.216	0.026	0.090	0.009	-0.025	-0.005
	(0.16)	(0.02)	(0.14)	(0.02)	(0.14)	(0.02)
Industry R&D	0.028	0.006	0.057	0.009	0.071	0.011
	(0.12)	(0.02)	(0.09)	(0.01)	(0.09)	(0.01)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,379	4,379	9,925	9,925	9,925	9,925
Adj. R-squared	0.164	0.134	0.148	0.115	0.116	0.088

Table 8. Supplier-Customer Geographic Proximity Surrounding Blockchain Legislation

This table shows regressions that explain the geographic proximity between suppliers and their customers surrounding the enactment of state legislation favorable to the in-state use of blockchain technology in business and commerce. The sample includes all firms in the main sample for which customer information is available in both the Compustat Customer Segments database and the CRSP/Compustat merged database. Observations in Panel A are at the supplier firm × year level, while observations in Panel B are at the supplier-customer pair × year level. In Panel A, *# of Nearby Cust.* is the number of nearby customers the supplier has in a given year, where nearby customers are defined as those headquartered within 50 (or 100) kilometers. *% of Nearby Cust.* is the percentage of nearby customers the supplier has in a given year. *Keep Any Nearby Cust.* indicates that the supplier keeps at least one nearby customer from the prior year. *Add Any Distant Cust.* is an indicator equal to 1 if the supplier adds at least one distant customer since the prior year. Distant customers are customers whose headquarters are located at least 300 (or 400) kilometers from the supplier's headquarters. Columns (1)-(4) employ firm-year observations in the main sample for which customer information is available. Columns (5)-(8) further drop observations where the "new customer" indicator does not apply. The new customer indicator equals 1 if the customer is newly added and 0 otherwise (it is not applicable for the first year in the sample in which a supplier starts to report its customer information). *# of Customers* is the number of major customers a supplier has in a given year. The main explanatory variable and the control variables are as described in Table 4. All regressions in Panel A include firm fixed effects and year fixed effects. Robust standard errors, clustered at the firm level, are reported in parentheses below coefficient estimates. In Panel B, *Pair Distance* is the distance between the supplier's headquarters and the customer's headquarters (in kilometers). *Nearby Pair* indicates that the distance between the supplier's headquarters and the customer's headquarters is less than 50 (or 100) kilometers. *Keep Nearby Pair* indicates that the pair is kept from last year and is a nearby pair. *Add Distant Pair* indicates that the pair is newly added this year and is a distant pair. A distant pair is one for which the distance between the supplier's headquarters and the customer's headquarters is at least 300 (or 400) kilometers. Columns (4)-(7) drop supplier-customer pairs where the new customer indicator does not apply. Supplier (customer) controls include the supplier's (customer's) *Size*, *ROA*, *Cash*, *Sales*, *HHI*, *Industry Intangibles,* and *Industry R&D*. All regressions in Panel B include supplier fixed effects, customer fixed effects, and year fixed effects. Robust standard errors, clustered at the supplier-customer pair level, are reported in parentheses below coefficient estimates. All continuous variables except for *ASI* are winsorized at the 1% and 99% levels. *# of Nearby Cust.*, *Pair Distance*, *Size*, *Industry Intangibles*, and *Industry R&D* are log-transformed. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 8, continued

Panel A: Supplier-Level Tests								
	# of Nearby Cust.		*% of Nearby Cust.*		*Keep Any Nearby Cust.*		*Add Any Distant Cust.*	
	< 50 km	< 100 km	< 50 km	< 100 km	< 50 km	< 100 km	≥ 300km	≥ 400 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Treat × ASI	-0.119**	-0.110**	-0.101**	-0.098*	-0.146**	-0.152**	0.214**	0.196*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.10)	(0.10)
Post Treat	0.077***	0.069**	0.071**	0.064*	0.092**	0.094**	-0.114*	-0.114*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.06)	(0.06)
Treat × ASI	0.068	0.097	0.063	0.056	-0.071	-0.079	-0.294	-0.273
	(0.12)	(0.13)	(0.10)	(0.11)	(0.14)	(0.14)	(0.21)	(0.20)
ASI	0.074	0.061	0.002	0.007	0.118	0.149	0.004	0.035
	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.16)	(0.15)
# of Customers	0.045***	0.052***			0.028***	0.028***	0.111***	0.103***
	(0.01)	(0.01)			(0.01)	(0.01)	(0.01)	(0.01)
Size	-0.005	-0.011	-0.002	-0.005	0.001	0.000	0.007	-0.000
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
ROA	0.013	0.014	0.025	0.021	0.015	0.009	0.002	0.010
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)
Cash	0.004	-0.017	0.012	0.002	-0.014	-0.021	0.023	-0.004
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)	(0.06)	(0.06)
Sales	-0.005	-0.003	0.002	0.004	0.012	0.017	-0.044*	-0.048**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
HHI	-0.050	-0.043	-0.017	-0.012	-0.019	-0.022	0.050	0.053
	(0.03)	(0.03)	(0.02)	(0.02)	(0.05)	(0.05)	(0.06)	(0.06)
Industry Intangibles	0.003	0.005	0.001	0.003	-0.002	-0.001	-0.010	-0.011
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Industry R&D	0.002	0.001	0.001	0.000	0.006	0.004	0.011*	0.011*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,327	7,327	7,327	7,327	7,200	7,200	7,200	7,200
Adj. R-squared	0.862	0.861	0.863	0.866	0.705	0.706	0.355	0.356

Continued on next page

Table 8, continued

Panel B: Pair-Level Tests							
	Pair Distance	*Nearby Pair*		*Keep Nearby Pair*		*Add Distant Pair*	
		< 50 km	< 100 km	< 50 km	< 100 km	≥ 300 km	≥ 400 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Treat × ASI	0.332**	-0.051**	-0.049*	-0.064**	-0.068**	0.157**	0.170***
	(0.14)	(0.03)	(0.03)	(0.03)	(0.03)	(0.07)	(0.07)
Post Treat	-0.182**	0.033**	0.027*	0.040**	0.036*	-0.077*	-0.089**
	(0.09)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)
Treat × ASI	-0.610**	0.050	0.025	-0.041	-0.072	-0.241*	-0.213
	(0.30)	(0.06)	(0.06)	(0.07)	(0.07)	(0.14)	(0.13)
ASI	0.392*	-0.015	-0.022	-0.004	0.010	0.085	0.079
	(0.21)	(0.04)	(0.05)	(0.05)	(0.06)	(0.11)	(0.10)
Control for # Customers	No	No	No	Yes	Yes	Yes	Yes
Supplier Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Customer Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Supplier FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Customer FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,304	15,304	15,304	14,929	14,929	14,929	14,929
Adj. R-squared	0.773	0.742	0.737	0.608	0.606	0.364	0.359

Internet Appendix for

"Can Blockchain Technology Help Overcome Contractual Incompleteness? Evidence from State Laws"

Part A. Lists of Terms for Identifying Blockchain-Related Patent Applications

To identify patent applications related to blockchain technology, we assemble lists of filtering terms that are semantically associated with blockchains or distributed ledgers. We compile these term lists by reading and systematically parsing several prominent articles from 2021 about blockchain and Bitcoin in *Wikipedia*, the *Wall Street Journal*, and the *Financial Times*. After collecting all unique terms that are potentially related to blockchain technology, we divide these terms into two groups based on whether a term is unambiguously associated with blockchain.[1] Terms that are ambiguously associated with the subject of blockchain are further classified according to whether a specific capitalization scheme is essential to the meaning of the term, such as in the case of proper names or acronyms. We present these term lists in Figure IA1.

We use our term lists to filter the full sample of patent application texts as follows. First, for each application, we search for an instance of a filtering term in the patent filing's Title or Abstract. If the Title and Abstract do not contain any filtering term, we exclude the patent application from further consideration. Next, we further screen the sample by requiring one or more filtering terms to appear in the Summary or Claims sections of the patent filing. In cases where the Title or Abstract contains an unambiguous term, we do not place any additional requirement on what type of filtering term (ambiguous or unambiguous) must appear in the Summary or Claims sections. However, if only one or more ambiguous terms appear in the Title and Abstract, we require the patent filing's Summary or Claims sections to contain an unambiguous term. Our final sample of blockchain-related patents are those that meet the above filtering requirements. In applying these filters, we count only full matches. That is, we do not register a match if a term is only part of an individual word in the filing, or if a filing word is only part of a filtering term.

[1] For example, "blockchain" and "decentralized ledgers" are deemed to be unambiguous terms. "Tokenization" and "mining pool," on the other hand, are considered to be ambiguous terms.

Figure IA1: Terms Related to Blockchain Technology

Unambiguous Terms
51 percent attack; 51% attack; altcoin; altcoins; atomic swap; atomic swaps; Auroracoin; Auroracoins; Bancor; Binance; bit gold; bitcoin; bitcoins; Bitconnect; bitFlyer; bitgold; Bithumb; BitInstant; BitLicense; BitMEX; BitPay; BitShares; Bitstamp; Bittrex; block chain; block explorer; block explorers; blockchain; BTC-e; Byzantine fault tolerance; CEX.io; coinbase; Coincheck; CoinCorner; Coinfloor; Coinrail; Coins.ph; colored coin; colored coins; consensus protocol; consensus protocols; crypto exchange; crypto exchanges; crypto token; crypto tokens; crypto-asset; crypto-assets; cryptocurrencies; cryptocurrency; crypto-exchange; crypto-exchanges; Cryptokitties; CryptoNight; CryptoNote; Cryptopia; cryptotoken; cryptotokens; decentralized ledger; decentralized ledgers; Digital Security Offering; distributed ledger; distributed ledgers; DLT account; DLT accounts; DLT address; DLT addresses; DLT network; DLT networks; DLT node; DLT nodes; DLT oracle; Dogecoin; Dogecoins; EOS.IO; Equihash; ERC-1155; ERC-20; ERC-721; Ethereum; Everledger; Filecoin; Filecoins; Gemini Trust; Ghash.io; Gridcoin; Gridcoins; hard fork; hard forks; hardfork; hardforks; hardware wallet; hardware wallets; Hashcash; Huobi; hyperledger; Initial Coin Offering; Initial Coin Offerings; Internet of Value; itBit; Lightning network; litecoin; litecoins; LocalBitcoins; Lyra2; Merkle root; Merkle roots; Merkle tree; Merkle trees; Monero; Mt. Gox; Nakamoto (2008); Namecoin; Namecoins; nonfungible token; non-fungible token; nonfungible tokens; non-fungible tokens; offchain oracle; off-chain oracle; offchain oracles; off-chain oracles; OKEx; orphan block; orphan blocks; peer to peer electronic cash; Peercoin; Peercoins; peer-to-peer electronic cash; permissioned chain; permissioned chains; permissionless DLT system; permissionless DLT systems; PotCoin; PotCoins; ppcoin; ppcoins; Primecoin; Primecoins; private DLT system; private DLT systems; proof of authority; Proof of Existence; proof of space; proof of stake; proof of work; proof-of-authority; Proof-of-Existence; proof-of-space; proof-of-stake; proof-of-work; public DLT system; public DLT systems; QuadrigaCX; Robocoin; Satoshi Nakamoto; Scrypt; Security Token Offering; Security Token Offerings; Segregated Witness; Segregated Witnesses; SegWit; SHA-256; SHA-3; ShapeShift; smart contract; smart contracts; soft fork; soft forks; softfork; softforks; stablecoin; stablecoins; Steem; Tezos; Upbit; Vertcoin; Vertcoins; XBT; Zcash; Zcoin; Zcoins; Zerocash; Zerocoin

Ambiguous Terms
airdrop; airdrops; application specific integrated circuit; application-specific integrated circuit; ASIC; block header; block reward; block time; blocktime; consensus algorithm; consensus mechanism; crypto-anarchism; cryptographic hash; cryptographic nonce; cryptography; dApp; Dapp; DApp; decentralized application; decentralized autonomous organization; Digicash; digital cash; digital currencies; digital currency; double spend; double spending; double-spend; double-spending; ecash; electronic cash; electronic money; emoney; field programmable gate array; field-programmable gate array; FPGA; genesis block; hashing power; mining pool; mining pools; Nakamoto; NEM; NEO; NXT; off-chain; off-ledger; P2P; peer to peer; peer-to-peer; permissionable; permissioned; Ripple Labs; Satoshi; subchain; The DAO; tokenization; virtual currencies; virtual currency; X11; zero knowledge proof

Additional Ambiguous Terms (Matching Capitalization is Required):
Kraken; Libra; Ripple; Stellar; Tether; ICO; ICOs

Part B. Robustness Tests based on Stacked Regressions

Baker, Larcker, and Wang (2022) show that staggered difference-in-differences estimators can be biased and can have different magnitudes or signs from true average treatment effects. Intuitively, the reason for the bias is that, when treatment effects can vary over time, already-treated observations function as improper controls that can drag the changes in later-treated units to an arbitrary level. To address this concern, we conduct robustness tests based on a stacked regression approach as recommended in Baker et al. (2022). For each blockchain legislation event, we assign a clean control group to the treated group (i.e., firms that experience the event). The clean control group includes both (1) firms that have not yet experienced any sample legislation event and (2) firms that never experience any legislation event in the sample. Some firms may experience more than one pro-blockchain law event during the sample period. For these cases, we only include the firm in the treated group if the relevant legislation is the earliest such law that the firm experiences. We construct a data-specific identifier and stack together the event-specific datasets. We then estimate triple-difference (DDD) regressions and control for firm × law fixed effects and year × law fixed effects.

Table IA1. Blockchain Legislation and Firm Value – Stacked Regressions

This table shows the results of regressions that explain firm value surrounding the enactment of state legislation favorable to the in-state use of blockchain technology in business and commerce. The sample consists of firm-event-year observations of CRSP/Compustat firms from 2011 to 2021 and is constructed following the "stacked regression" approach as suggested by Baker, Larcker, and Wang (2022). Details on the sample construction are described in Section 4 of the paper. In Column (1), the dependent variable *Tobin's Q* is calculated from Compustat items as (PRCC_F × CSHO + AT – CEQ) / AT. In Column (2), the dependent variable is an alternative measure of Tobin's Q, which is calculated from Compustat items as (DLTT + DLC + PRCC_F × CSHO – ACT) / PPEGT. Columns (3) and (4) are at the quarterly level, and the dependent variables for these columns correspond to the Tobin's Q measures in Columns (1) and (2), respectively. In Column (4), missing annual values of PPEGT are replaced with PPEGTQ in the fourth quarter of the same fiscal year, if available. In Columns (2) and (4), observations are dropped if the annual PPEGT is less than $5 million. The main explanatory variables are as described in Table 3 and Table 4. *Controls* include *Size*, *ROA*, *Cash*, *Sales*, *HHI*, *Industry Intangibles*, and *Industry R&D*, and are as described in Table 4. All continuous variables except for *ASI* are winsorized at the 1% and 99% levels. *Tobin's Q*, *Tobin's Q Alt.*, *Tobin's Q, Quarterly, Tobin's Q Alt., Quarterly, Size*, *Industry Intangibles*, and *Industry R&D* are log-transformed. All regressions include firm × law fixed effects and year × law fixed effects. Robust standard errors, clustered at the firm × law level, are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	Tobin's Q	*Tobin's Q Alt.*	*Tobin's Q, Quarterly*	*Tobin's Q Alt., Quarterly*
	(1)	(2)	(3)	(4)
Post Treat × ASI	0.152***	0.270***	0.136***	0.293***
	(0.03)	(0.07)	(0.03)	(0.07)
Post Treat	-0.085***	-0.155***	-0.071***	-0.132***
	(0.02)	(0.04)	(0.01)	(0.04)
Treat × ASI	-0.128***	-0.288**	-0.127***	-0.194
	(0.05)	(0.13)	(0.04)	(0.12)
ASI	0.116***	0.283***	0.094***	0.065
	(0.01)	(0.05)	(0.01)	(0.04)
Controls	Yes	Yes	Yes	Yes
Firm × Law FEs	Yes	Yes	Yes	Yes
Year × Law FEs	Yes	Yes	No	No
Quarter × Law FEs	No	No	Yes	Yes
Observations	250,537	200,589	1,022,601	520,976
Adj. R-squared	0.766	0.848	0.813	0.870

Table IA2. Blockchain Legislation and Innovation – Stacked Regressions

This table shows the results of regressions that explain firms' innovation activity following the passage of legislation favorable to the in-state use of blockchain technology in business and commerce. The sample consists of firm-event-year observations of CRSP/Compustat firms from 2011 to 2021 and is constructed following the "stacked regression" approach suggested by Baker, Larcker, and Wang (2022). Details on the sample construction are described in Section 4 of the paper. *R&D Intensity* is defined as R&D expenditures over sales. Missing values of R&D are treated as missing. *All Patents* is the total number of patent applications filed in a given year. *Blockchain Patents* is the number of blockchain patent applications filed in a given year. Blockchain patents are identified as described in Section 3.4 of the paper. *Patent Value* is the average value of all patent applications filed in a given year and is set as 0 if the firm does not file any patents in a given year. The value of a patent application is calculated following the method of Kogan et al. (2017) as described in Section 5.2.1 of the paper. *Patent Generality* is the average of patent generality across all patents filed by the firm in a given year, while the generality of a patent is measured as one minus the Herfindahl Index of the international patent classification (IPC) codes across all other patents that cite it (it is set to 0 if the firm does not file any patents during the year). Data on patent applications and citations are obtained from the USPTO database. Firm years with no patent application record in the USPTO database are counted as zero. The main explanatory variables are defined as described in Table 3 and Table 4. Controls include *Size*, *ROA*, *Cash*, *Sales*, *HHI*, *Industry Intangibles*, and *Industry R&D*, which are as described in Table 4. The *All Patents* variable and all continuous variables (except for *ASI*) are winsorized at the 1% and 99% levels. *R&D Intensity*, *All Patents*, *Blockchain Patents*, *Patent Value*, *Size*, *Industry Intangibles*, and *Industry R&D* are log-transformed. All regressions include firm × law fixed effects and year × law fixed effects. Robust standard errors, clustered at the firm × law deal level, are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	R&D Intensity	*All Patents*	*Blockchain Patents*	*Patent Value*	*Patent Generality*
	(1)	(2)	(3)	(4)	(5)
Post Treat × ASI	0.056*	-0.079	0.083***	0.796**	-0.151***
	(0.03)	(0.07)	(0.03)	(0.36)	(0.02)
Post Treat	-0.021	0.037	-0.026**	-0.368*	0.072***
	(0.02)	(0.04)	(0.01)	(0.20)	(0.01)
Treat × ASI	0.109**	-0.058	0.027	-1.052*	0.092***
	(0.05)	(0.12)	(0.03)	(0.58)	(0.03)
ASI	-0.109***	0.133***	0.009***	0.395***	-0.044***
	(0.02)	(0.03)	(0.00)	(0.14)	(0.01)
Controls	Yes	Yes	Yes	Yes	Yes
Firm × Law FEs	Yes	Yes	Yes	Yes	Yes
Year × Law FEs	Yes	Yes	Yes	Yes	Yes
Observations	148,917	250,804	250,804	250,804	250,804
Adj. R-squared	0.812	0.876	0.220	0.706	0.521

Table IA3. Blockchain Legislation and Vertical Integration Activity – Stacked Regressions

This table shows the results of regressions that explain firms' vertical integration activity following the passage of legislation favorable to the in-state use of blockchain technology in business and commerce. The sample consists of firm-event-year observations of CRSP/Compustat firms from 2011 to 2021 and is constructed following the "stacked regression" approach suggested by Baker, Larcker, and Wang (2022). *High (Low) Vertical Integration* is an indicator equal to 1 if a firm's vertical integration score in a given year is greater than or equal to the 75th percentile (less than or equal to the 25th percentile) of the overall sample. The vertical integration score is drawn from Frésard, Hoberg, and Phillips (2020) (downloaded from the Frésard-Hoberg-Phillips Vertical Relatedness Data Library as of April 2023). *All M&A Deals* is the total number of M&A deals a firm announces in a given year. An M&A deal is counted when both the target firm and the acquirer are included in the CRSP/Compustat merged data. *High (Low) Vertical Relatedness Deals* is the number of M&A deals for which the focal firm and counterparty of the deal have a high-level (low-level) supplier-customer relationship and the focal firm is the potential supplier. Supplier-customer relationships are defined based on the 2012 I-O table (details provided in Section 5.2.2). M&A deals are measured as of the year following a given fiscal year end. Data on M&A deals are obtained from Thomson Reuters SDC database and aggregated at the yearly level. Firm-years with no reported M&A in the SDC Platinum database are counted as zero. The main explanatory variables are defined as described in Table 3 and Table 4. Controls include *Size*, *ROA*, *Cash*, *Sales*, *HHI*, *Industry Intangibles*, and *Industry R&D*, and are as described in Table 4. All continuous variables except for *ASI* are winsorized at the 1% and 99% levels. *Size*, *Industry Intangibles*, and *Industry R&D* are log-transformed. All regressions include firm × law fixed effects and year × law fixed effects. Robust standard errors, clustered at the firm × law level, are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	Low Vertical Integration	*High Vertical Integration*	*All M&A Deals*	*High Vertical Relatedness Deals*	*Low Vertical Relatedness Deals*
	(1)	(2)	(3)	(4)	(5)
Post Treat × ASI	0.075**	-0.097***	-0.042**	-0.031**	-0.008
	(0.03)	(0.04)	(0.02)	(0.02)	(0.01)
Post Treat	-0.058***	0.059***	0.007	0.006	0.000
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Treat × ASI	-0.062	-0.173***	0.035	0.049**	-0.015
	(0.06)	(0.06)	(0.03)	(0.02)	(0.02)
ASI	0.067***	0.111***	-0.077***	-0.055***	-0.017***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Controls	Yes	Yes	Yes	Yes	Yes
Firm × Law FEs	Yes	Yes	Yes	Yes	Yes
Year × Law FEs	Yes	Yes	Yes	Yes	Yes
Observations	250,451	250,451	250,804	250,804	250,804
Adj. R-squared	0.687	0.774	0.122	0.119	0.129

Table IA4. Blockchain Legislation and Alliances – Stacked Regressions

This table shows the results of regressions that explain firms' strategic alliance and joint venture formation following the passage of legislation favorable to the in-state use of blockchain technology in business and commerce. The sample consists of firm-event-year observations of CRSP/Compustat firms from 2011 to 2021 and is constructed following the "stacked regression" approach as suggested by Baker, Larcker, and Wang (2022). Details on the sample construction are described in Section 4 of the paper. Data on alliances are obtained from Thomson Reuters SDC database. We include deals where at least one participant-year observation is covered by CRSP/Compustat merged database. *All Alliance Deals* is the total number of alliance deals announced in a given year. *Strategic Alliance Deals* is the number of alliance deals announced in a given year that are identified as strategic alliances by SDC database. *High-Tech Strategic Alliance Deals* is the number of strategic alliance deals where at least one partner firm's primary NACIS code belongs to a high-tech industry. The definition of high-tech industries is as described in Table 7. *Avg. CAR* is the average of the (0, +1) announcement CARs of all alliance deals announced in a given year, multiplied by 100. Each announcement CAR is scaled by the number of deals announced on the same event day. *Avg. Value* is the average of value of all alliance deals announced in a given year, where deal value is calculated as the product of the 2-day announcement CAR and the firm's log-transformed market capitalization 5 trading days prior to the announcement. The main explanatory variables are as described in Table 3 and Table 4. Controls include *Size*, *ROA*, *Cash*, *Sales*, *HHI*, *Industry Intangibles*, and *Industry R&D*, and are as described in Table 4. All continuous variables except for *ASI* are winsorized at the 1% and 99% levels. *All Alliance Deals*, *Strategic Alliance Deals*, *High Tech Strategic Alliance Deals*, *Size*, *Industry Intangibles*, and *Industry R&D* are log-transformed. All regressions include firm × law fixed effects and year × law fixed effects. Robust standard errors, clustered at the firm × law level, are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	All Alliance Deals (1)	*Strategic Alliance Deals* (2)	*High-Tech Strategic Alliance Deals* (3)	*Avg. CARs* (4)	*Avg. Value* (5)
Post Treat × ASI	0.171***	0.145***	0.148***	2.832***	0.395***
	(0.04)	(0.04)	(0.03)	(0.98)	(0.13)
Post Treat	-0.076***	-0.038*	-0.077***	-2.194***	-0.293***
	(0.02)	(0.02)	(0.01)	(0.61)	(0.08)
Treat × ASI	-0.084	-0.018	-0.041	2.390	0.320
	(0.07)	(0.06)	(0.04)	(1.79)	(0.25)
ASI	0.031**	0.011	-0.010	-0.411	-0.071
	(0.01)	(0.01)	(0.01)	(0.89)	(0.11)
Controls	Yes	Yes	Yes	Yes	Yes
Firm × Law FEs	Yes	Yes	Yes	Yes	Yes
Year × Law FEs	Yes	Yes	Yes	Yes	Yes
Observations	250,804	250,804	250,804	28,050	28,050
Adj. R-squared	0.359	0.312	0.326	0.145	0.126

Table IA5. Supplier-Customer Geographic Proximity Surrounding Blockchain Legislation – Stacked Regressions

This table shows the results of regressions that explain the geographic proximity between suppliers and their customers surrounding the enactment of state legislation favorable to the in-state use of blockchain technology in business and commerce. The sample includes all firms in the main sample whose customer information is available in both the Compustat Customer Segments database and the CRSP/Compustat merged database during the sample period. The sample is constructed following the "stacked regression" approach as suggested by Baker, Larcker, and Wang (2022). Details on the sample construction are described in Section 4 of the paper. For a given year, observations in Panel A are at the supplier firm-year-event level, while observations in Panel B are at the supplier customer pair-year-event level. In Panel A, *# of Nearby Cust.* is the number of nearby customers the supplier has in a given year, where nearby customers are defined as those headquartered within 50 (or 100) kilometers. *% of Nearby Cust.* is the percentage of nearby customers the supplier has in a given year. *Add Any Distant Cust.* is an indicator equal to 1 if the supplier adds at least one distant customer since the prior year. Distant customers are customers whose headquarters are located at least 300 (or 400) kilometers from the supplier's headquarters. Columns (1)-(4) employ firm-year observations in the main sample for which customer information is available. Columns (5)-(8) further drop observations where the "new customer" indicator does not apply. The new customer indicator equals 1 if the customer is newly added from the prior year, and 0 otherwise (it is not defined for the first year in the sample that a supplier starts to report its customer information). *# of Customers* is the total number of reported customers that a supplier has in a given year. The main explanatory variable and other control variables are as described in Table 4. All regressions in Panel A include firm × law fixed effects and year × law fixed effects. Robust standard errors, clustered at the firm × law level, are reported in parentheses below coefficient estimates. In Panel B, *Pair Distance* is the distance between the supplier's headquarters and the customer's headquarters (in kilometers). *Nearby Pair* indicates that the distance between the supplier's headquarters and the customer's headquarters is less than 50 (or 100) kilometers. *Keep Nearby Pair* indicates the pair is kept from last year and is a nearby pair. *Add Distant Pair* indicates the pair is newly added this year and is a distant pair. Distant Pair indicates that the distance between the supplier's headquarters and the customer's headquarters is at least 300 (or 400) kilometers. Columns (4)-(7) drop supplier-customer pairs where the new customer indicator is missing. Supplier (Customer) Controls include the supplier's (customer's) *Size*, *ROA*, *Cash*, *Sales*, *HHI*, *Industry Intangibles,* and *Industry R&D*. All regressions in Panel B include supplier × law fixed effects, customer × law fixed effects, and year × law fixed effects. Robust standard errors, clustered at the law × supplier-customer pair level, are reported in parentheses below coefficient estimates. All continuous variables except for *ASI* are winsorized at the 1% and 99% levels. *# of Nearby Cust.*, *Pair Distance*, *Size*, *Industry Intangibles*, and *Industry R&D* are log-transformed. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A: Supplier-Level Tests

	# of Nearby Cust.		*% of Nearby Cust.*		*Keep Any Nearby Cust.*		*Add Any Distant Cust.*	
	< 50 km	< 100 km	< 50 km	< 100 km	< 50 km	< 100 km	≥ 300km	≥ 400 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Treat × ASI	-0.125***	-0.117**	-0.100**	-0.098*	-0.147***	-0.157***	0.209**	0.194*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.10)	(0.10)
Post Treat	0.080***	0.073**	0.072**	0.064*	0.093***	0.097**	-0.086	-0.088
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.06)	(0.06)
Treat × ASI	0.114	0.151*	0.100*	0.089	-0.035	-0.014	-0.351**	-0.334**
	(0.08)	(0.09)	(0.06)	(0.06)	(0.10)	(0.10)	(0.15)	(0.15)
ASI	0.047**	0.024	-0.022	-0.017	0.099***	0.097***	0.056	0.090**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)

Continued on next page

Table IA5, continued

Control for # Customers	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Law FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Law FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59,049	59,049	59,049	59,049	57,924	57,924	57,924	57,924
Adj. R-squared	0.883	0.884	0.853	0.862	0.696	0.693	0.371	0.371

Panel B: Pair-Level Tests

	Pair	*Nearby Pair*		*Keep Nearby Pair*		*Add Distant Pair*	
	Distance	< 50 km	< 100 km	< 50 km	< 100 km	≥ 300 km	≥ 400 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Treat × ASI	0.309**	-0.059**	-0.057**	-0.081***	-0.090***	0.225***	0.219***
	(0.13)	(0.03)	(0.03)	(0.03)	(0.03)	(0.07)	(0.07)
Post Treat	-0.169**	0.036**	0.030*	0.034*	0.029	-0.074*	-0.081**
	(0.08)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)
Treat × ASI	-0.543***	0.061*	0.044	-0.072	-0.082	-0.221**	-0.191*
	(0.19)	(0.03)	(0.04)	(0.05)	(0.05)	(0.10)	(0.10)
ASI	0.366***	-0.038***	-0.054***	0.017	0.007	0.053*	0.054*
	(0.05)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)
Control for # Customers	No	No	No	Yes	Yes	Yes	Yes
Supplier Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Customer Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Supplier × Law FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Customer × Law FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Law FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	120,715	120,715	120,715	117,754	117,754	117,754	117,754
Adj. R-squared	0.807	0.781	0.777	0.624	0.621	0.409	0.401