**The Impact of Blockchain-enabled Smart Contracts on Firms’** **Operational Efficiency[[1]](#footnote-1)**

**Abstract**

Smart contracts, enabled by blockchain technology, are increasingly adopted by firms to automate the execution of agreements or contracts without the involvement of intermediaries. However, it is still largely unclear how smart contracts may affect firms’ operational efficiency. We answer this question by empirically conducting a quasi-natural experiment in the United States in which certain states have enacted relevant laws that increase in-state firms’ propensity to adopt and use smart contracts. Our difference-in-differences estimation suggests that compared with out-of-state control firms, in-state treatment firms’ operational efficiency increases significantly after the enactment of smart contract laws. Our additional analysis further suggests that state-level smart contract laws help increase in-state firms’ actual smart contract activities, which would in turn lead to operational efficiency improvement. We also find that the operational efficiency improvement varies across firms with different supply chain complexities. While firms with a large number of supply chain partners (i.e., high horizontal complexity) gain more operational efficiency improvement, the improvement level becomes less pronounced if firms’ supply chain partners are distributed across different countries (i.e., high spatial complexity). Overall, our research demonstrates smart contracts’ ability to improve operational efficiency but also reveals the critical role of supply chain complexity in affecting the operational efficiency improvement.

*Keywords*: smart contract, operational efficiency, supply chain complexity, quasi-natural experiment, difference-in-differences estimation

**1. Introduction**

Over the past few years, the advent of blockchain technology has given rise to smart contracts, a revolutionary digital innovation (Choi et al., 2022). A blockchain-based smart contract is a self-executing contract built on decentralized platforms and supported by a blockchain system with the terms of the agreement directly written into codes (Cong and He, 2019; Ferreira, 2021). Supply chain operations have become an important use case for smart contracts owing to the high volume of engagements among multiple parties in this context. For example, AgUnity is a technology platform that leverages blockchain-enabled smart contracts to empower smallholder farmers to access market information such as price and past transactions, eliminating the need for personal trust among involved parties (Schmidt and Wagner, 2019). Additionally, the shipping and logistics sector has seen great potential in the adoption of smart contracts due to its complex, multi-party nature and the high volume of documentation involved (Cong and He, 2019). For example, to move a container at the Port of Antwerp, there are on average 200 different interactions amongst 30 parties (GEP, 2022). With smart contract solutions provided by blockchain-based platforms such as CargoX, every transaction and movement of goods can be recorded and tracked on a shared ledger that is visible and verifiable by all participants, which can enhance transparency, automation, security, and scalability in the global trade.

Despite the increasing popularity of smart contracts in real-world applications, how their adoption would affect firms’ operational efficiency is still unclear. On the one hand, smart contracts may improve operational efficiency through reducing transaction costs, mitigating firm risks, and enhancing interfirm relationships. For example, smart contracts may lower the working capital requirements and simplify finance operations for supply chain partners, because payments will be automatically triggered once conditions (e.g., containers reach customers) are met, thus eliminating the procure-to-pay gaps and the need for intermediaries such as banks (Olsen and Tomlin, 2020). Automated transactions not only speed up transaction processes but also reduce transaction risks by limiting the opportunistic behavior of supply chain partners and mitigating the effect of behavioral and environmental uncertainties (Lumineau et al., 2021). By creating a tamper-proof and permanent record of transactions, smart contracts can enhance transparency and system trust among supply chain partners, reducing the risk of misunderstandings and facilitating long-term relationships (Schmidt and Wagner, 2019). Altogether, by fostering increased transparency along the supply chain and enhanced information sharing between supply chain partners, smart contracts facilitate a more efficient flow of products, finances, and information, thus improving operational efficiency (Tapscott and Tapscott, 2017; Schmidt and Wagner, 2019; Babich and Hilary, 2020; Kumar et al., 2018).

On the other hand, the realization of the aforementioned benefits is contingent on the successful implementation of smart contracts among supply chain partners, which can face several challenges in reality. In particular, smart contracts are not merely standalone tools that are implemented within firms but contracting and technology links that involve multiple organizations. Moreover, while the removal of intermediaries (e.g., banks) enabled by smart contracts leads to streamlined processes and efficient transactions, it may create another layer of complexity and uncertainty (Cong et al., 2023; Lumineau et al., 2021). This suggests that convincing supply chain partners to participate in the blockchain network and implement smart contracts may not be an easy task. Dominant parties who intend to behave opportunistically or benefit from power asymmetry may lack the incentive to participate in the blockchain network (Schmidt and Wagner, 2019). Moreover, integration with existing systems is not cost-free. Many firms already have established processes and systems in place, and integrating smart contracts into these systems may require significant time, effort, and financial investments (Ferreira, 2021). Another potential concern is data privacy. As blockchain transactions are publicly recorded, sensitive information may be exposed if not properly encrypted, making it difficult to comply with data privacy regulations (Ferreira, 2021). Lastly, the legal and regulatory framework surrounding smart contracts is still evolving, and legal status of smart contracts can be ambiguous in some countries. Firms may need to invest in legal and managerial expertise to ensure compliance with local laws and regulations. Therefore, whether smart contracts will have a positive or negative impact on firms’ operational efficiency remains an empirical research question.

Empirical investigation of the impact of smart contracts on firms’ operational efficiency is particularly challenging due to limited data availability and potential endogeneity concerns. As far as we know, there is no existing database that documents the details of firms’ smart contract adoption. It is also uncommon for firms to disclose details about their smart contract adoption publicly, possibly because the technology is still relatively immature (Carson et al., 2018; Ferreira, 2021) and firms may want to avoid making strong public commitments to a still-emerging technology. Additionally, firms’ smart contract adoption and operational efficiency may codetermine each other such that firms’ operational efficiency may affect their propensity of adopting smart contracts, leading to reverse causality concerns. Moreover, unobserved factors such as supply chain relationships and competitive pressure may simultaneously affect firms’ smart contract adoption and operational efficiency, causing omitted variable biases.

To overcome these methodological challenges, we leverage a quasi-natural experiment based on the staggered enactment of state-level laws related to smart contracts in the United States (US). We identify five states, namely Arizona, Tennessee, North Dakota, South Dakota, and Arkansas, where smart contract laws were enacted between 2017 and 2019. These laws generally recognize the legal authority to use smart contracts in conducting electronic transactions, lowering the costs of developing and using smart contracts for business and commerce (Ferreira, 2021; Chen et al., 2023). We then perform a difference-in-differences (DID) analysis to compare the differences in operational efficiency changes between treatment firms operating in these five states and the “matched control firms” that are identified as those in the same industry (two-digit SIC code) but located in other US states using the Mahalanobis Distance Matching (MDM) approach. With this approach, we can address the data availability issues and endogeneity concerns to investigate the causal impact of smart contracts on firms’ operational efficiency.

Our DID test results indicate that compared to out-of-state matched control firms, in-state treatment firms’ operational efficiency increases significantly after their states have enacted smart contract laws over a maximum of five-year period after the enactment. This finding remains consistent across various robustness checks with alternative estimation methods, variable measurements, and matching approaches. Our post hoc analyses based on secondary data manually collected from multiple sources further suggest that state-level smart contract laws help increase in-state firms’ smart contract activities in terms of adopting smart contracts and recruiting smart contract talents, which in turn lead to operational efficiency improvement. We also test three channels (i.e., cost reduction, risk mitigation, and relationship enhancement) through which smart contracts improve firms’ operational efficiency. In particular, our test results reveal that smart contracts not only help firms reduce costs related to overall operations, production, sales, and inventory activities, but also enhance firms’ relationships with supply chain partners, ultimately leading to operational efficiency improvement.

We further find that the operational efficiency improvement arising from smart contracts varies across firms with different levels of supply chain complexity. While firms with a large number of supply chain partners (i.e., high horizontal supply chain complexity) experience greater operational efficiency improvement, the improvement is less pronounced for firms whose supply chain partners are distributed across countries (i.e., high spatial supply chain complexity). However, the operational efficiency improvement is independent of whether firms’ supply chain partners are closely connected to each other (high interconnected supply chain complexity).

Our study makes several important contributions to the operations management (OM) literature and practices. First, to the best of our knowledge, our study is the first empirical quantitative investigation of the impact of smart contracts on firms’ operational efficiency. While there are qualitative discussions (Lumineau et al., 2021) and analytical analysis (Wang et al., 2021; Dong et al., 2023; Lee et al., 2023) of the pivotal role of smart contracts in supply chain management, quantitative investigation is lacking in the literature due to limited data availability and potential endogeneity concerns. Our research addresses this challenge by employing a rigorous approach based on a quasi-natural experiment setting where smart contract laws were enacted between 2017 and 2019 in five US states. We have also collected additional data and verified that the enactment of state-level smart contract laws does increase in-state firms’ actual smart contract activities, providing a solid empirical foundation for OM researchers to employ our approach to examine the impact of smart contracts on other operational outcomes.

Moreover, our research opens the “black box” of the smart contract-operational efficiency relationship by theoretically arguing and empirically testing the channels through which smart contracts affect firms’ operational efficiency. These investigations help advance our understanding of the potential impact of adopting smart contracts and provide important implications for future smart contract research.

Finally, our findings highlight how the complexities of firms’ supply chains may induce different opportunities and challenges for the operational efficiency improvement arising from smart contracts. These insights are particularly important for practitioners and policymakers as they navigate the complexities of implementing smart contracts in a globalized world.

**2. Literature and Hypothesis Development**

**2.1 Blockchain-enabled Smart Contracts**

Essentially, a smart contract is a self-executing if–then agreement with the terms and conditions directly embedded into code, running on a decentralized blockchain platform (Cong and He, 2019; Ferreira, 2021). Prior research has explored some key functionalities of smart contracts. For instance, Cong and He (2019) highlight that smart contracts are neither merely digital contracts that involve high degrees of human intervention and centralized authority, nor merely an automation technology such as robots. Instead, smart contracts contain the key functionalities of both supply chain contracts (in the format of digital contracts) and advanced technology. Olsen and Tomlin (2020) and Lee et al. (2023) focus on smart contracts’ automation features and show how the computerized functions specified in smart contracts could be automatically triggered and executed. Zhao et al. (2022) explore the technology properties of transactions in smart contracts, elaborating why the transaction information could be transparent, traceable, and immutable. Overall, these studies demonstrate how smart contracts are different from traditional supply chain contracts.

Many studies have discussed the potential benefits or advantages of adopting smart contracts (Wang and Xu, 2023; Malik et al., 2023; Chod and Lyandres, 2023). For example, the accurate information guaranteed by smart contracts can help combat counterfeits (Malik et al., 2023), provide digital evidence in the e-government or e-justice systems (Petroni et al., 2020), and enable firms to gain advantages in product market competition (Chod and Lyandres, 2023). Their superior performance of enhancing transparency and traceability can reduce operational costs related to contractual incompleteness (Pereira et al., 2019). For example, smart contracts can address challenges associated with information overload (Shahab and Allam, 2020), uncooperative behaviors of transaction partners (Lumineau et al., 2021), and the trust concerns among these partners (Kurpjuweit et al., 2021; Kordestani et al., 2023), all common in traditional supply chain contracting.

Conversely, other studies have examined the challenges in smart contract adoptions (Wang et al., 2021; Liu et al., 2023; Chang et al., 2019). For example, smart contracts may be exploited by attackers. This will cause financial damages if the extant vulnerability detection technology cannot locate which function in a smart contract is vulnerable (Liu et al., 2023). Chang et al. (2019) also find that limited understanding among firms of smart contract impedes its widespread adoption. Legal uncertainties and implementation costs are also major concerns. Thus, while promising, smart contracts carry significant risks and uncertainties.

Despite the growing academic interest, there is still limited understanding of the implications of smart contract adoption for firm-level operational outcomes. In addition, most prior smart contract studies have focused on theoretical modeling (e.g., Wang et al., 2021; Wang and Xu, 2023; Chod and Lyandres, 2023) and conceptual analysis (e.g., Chang et al., 2019; Pereira et al., 2019; Petroni et al. 2020; Shahab and Allam, 2020; Lumineau et al., 2021), providing little quantitative-empirical evidence. Therefore, our research aims to quantitatively examine how smart contracts affect firms’ operational efficiency, an important firm-level operational outcome (Lam et al., 2016; Li et al., 2022; Shen et al., 2023).

**2.2 The Impact of Smart Contracts on Operational Efficiency**

We adopt the theoretical lens of Transaction Cost Economics (TCE) (Williamson, 1985; 1989) to explain the impact of smart contracts on firms’ operational efficiency. TCE examines the optimal governance decisions that minimize transaction costs under specific conditions (Schmidt and Wagner, 2019) and its logic is regarded as “a theory of supply chain efficiency” (Ketokivi and Mahoney, 2020, p. 1011).

By focusing on “transactions” and “contracting” (Grover and Malhotra, 2003), TCE is regarded as an appropriate theoretical perspective to the context of blockchain and smart contracts (Schmidt and Wagner, 2019). Traditional contracts often suffer the incompleteness problem, as parties cannot foresee all future contingencies, leading to costly renegotiations and opportunistic behaviors (Hart, 1989). In contrast, smart contracts mitigate these inefficiencies by automating enforcement and minimizing contractual ambiguities. We explain how smart contract adoption may enhance operational efficiency from a TCE perspective, with a focus on transaction cost reduction, firm risk mitigation, and interfirm relationship enhancement. Transaction costs typically arise during negotiation, execution, monitoring, and enforcement of contracts, and risks may occur when parties fail to fulfill their agreed-upon responsibilities (Grover and Malhotra, 2003). In addition to transaction costs and risks, trust is often regarded as a valuable substitute for formal contracts and controls and a crucial element in successful interfirm relationships (Grover and Malhotra, 2003; Schmidt and Wagner, 2019). Next, we detail how smart contracts help reduce costs, mitigate risks, and enhance relationships through the TCE lens.

Transaction costs typically include activities such as identifying partners, negotiating terms, monitoring performance, and enforcing agreements (Grover and Malhotra, 2003; Schmidt and Wagner, 2019). In traditional contracting, these activities are exacerbated by the lack of contractual completeness, requiring firms to engage in costly renegotiations. For instance, in a manufacturer-supplier dyad, negotiation costs usually involve costs of exchanging information on products, price, availability, and demand (Lumineau et al., 2021). Smart contracts, utilizing standardized templates and predefined clauses, can streamline negotiations, reducing the time and effort required and automating repetitive tasks. Since smart contracts are coded with precise terms, they minimize ambiguity or the potential for misinterpretation, thus accelerating the agreement process and lowering the negotiation costs. Additionally, the real-time transparency enabled by smart contracts can reduce the monitoring and enforcement costs, as agreed-upon terms are automatically executed. For instance, payments can be released automatically when prespecified conditions are met, reducing the need for manual interventions and continuous oversight (Schmidt and Wagner, 2019).

TCE highlights the risks of opportunistic behavior, where transaction parties exploit information asymmetry or contractual gaps to their own advantages (Williamson, 1985). By implementing smart contracts, firms can limit such opportunistic behavior of supply chain partners (Schmidt and Wagner, 2019; Lumineau et al., 2021). For example, a buyer might overstate the demand for a product to negotiate a lower price, or a supplier might exaggerate the costs associated with design changes to charge higher prices. However, smart contracts establish an immutable and permanent record, potentially including past transactions and realized demand, thus rendering misbehavior detectable and traceable (Tapscott and Tapscott, 2017; Schmidt and Wagner, 2019; Lumineau et al., 2021). Transaction risks also emerge when parties evade agreed-upon responsibilities (Williamson, 1989). For example, in a manufacturer-supplier dyad, once a supplier makes the investment, the manufacturer may demand price concessions and other advantages to exploit the supplier’s sunk investment. Smart contracts can reduce the pressure and transaction risks exerted by the dominant party by setting prices under dynamic conditions and enforcing its execution once prespecified conditions are met (Schmidt and Wagner, 2019; Lee et al., 2023). This can be particularly beneficial in industries where severe power asymmetry exists, and asset specificity is high.

Long-term interfirm relationships are often difficult to establish due to the heightened transaction costs and risks in the absence of personal (relational) trust. This is especially true under environmental uncertainty, defined as unpredictability in the business environment such as demand volume and variety, as well as changes in technology, economy, and regulations (Grover and Malhotra, 2003). With bounded rationality, firms are unable to anticipate all possible scenarios, and the supply and demand parameters are largely unknown. Therefore, continuous renegotiation and adaptation are often necessary, leading to substantial transaction costs. Smart contracts enhance contractual completeness by fostering system trust with an automated and tamperproof system, which eliminates the need for personal trust between supply chain partners, thus mitigating the impact of such uncertainties (Schmidt and Wagner, 2019) and facilitating long-term relationships. For example, if a parameter for exchange is subject to new regulations, the blockchain network could automatically update all smart contracts to adhere to the new rules, eliminating the need for each party’s approval and negating any pressure by the power party, thus reducing the potential for disputes and frictions in the relationship (Gozman et al., 2020). Instead of relying on personal trust, the network itself functions as a trusted third party that validates transactions and prices. By embedding self-executing contractual mechanisms, smart contracts mitigate contract incompleteness, reducing the likelihood of opportunistic renegotiations.

Altogether, faster transactions facilitated by reduced intermediaries and automated processes may lead to shorter business cycles and reduced coordination costs. By limiting opportunistic behavior of supply chain partners and mitigating contract incompleteness, transaction risks can be substantially decreased and greater system trust is generated. Along with the reduced transaction costs, human and financial resources can be allocated to more value-adding tasks, thus improving overall operational efficiency. With the above arguments, we hypothesize that the adoption of smart contracts can lead to operational efficiency improvement:

*H1: Smart contracts have a positive impact on firms’ operational efficiency.*

**2.3 The Moderating Effects of Supply Chain Complexity**

While smart contracts can enhance supply chain transparency, reduce transaction costs, and improve operational efficiency, the realization of their full potential depends on partner onboarding, which in turn is shaped by factors such as power asymmetry, integration costs, data privacy concerns, and regulation ambiguities (Schmidt and Wagner, 2019; Babich and Hilary, 2020). These challenges motivate us to further examine how the impact of smart contracts may vary across firms. We aim to identify factors that enable firms to achieve greater potential of smart contracts or render firms to encounter more challenges in the implementation. We take an OM perspective and focus on supply chain complexity due to its relevance to transaction costs, contract completeness, and the aforementioned implementation challenges (Choi and Krause, 2006; Bode and Wagner, 2015; Chae et al., 2019; Gualandris et al., 2021; Lu and Shang, 2017, Wiedmer et al., 2021). Supply chain complexity is associated with the number of a firm’s supply chain partners, the degree of differentiation of the partners, and the level of interactions among them (Choi and Krause, 2006). From a contract theory perspective, complexity often exacerbates contractual incompleteness, leading to costly renegotiations and opportunistic behavior (Iyer and Schoar, 2010; Frydlinger and Hart, 2024). Smart contracts, by encoding comprehensive contractual clauses and automating execution, can mitigate such inefficiencies and enhance supply chain coordination.

Consistent with previous research, we characterize supply chain complexity as a multi-dimensional concept and focus on three dimensions: (1) horizontal complexity, which is the number of direct supply chain partners[[2]](#footnote-2) (Choi and Krause, 2006; Bode and Wagner, 2015); (2) spatial complexity, which is the geographical spread of these supply chain partners (Bode and Wagner, 2015); and (3) interconnected complexity, which is the level of inter-relationships among the supply chain partners (Choi and Krause, 2006). This characterization is adopted here because firms with greater horizontal and interconnected complexity can be associated with higher ex ante transaction costs, greater contractual incompleteness, and lower implementation barriers, and thus benefit more from smart contract adoption. However, greater spatial complexity may imply greater implementation barriers and compromise the potential of smart contracts.

**2.3.1 Horizontal Complexity**

Greater horizontal complexity is associated with a larger number of direct supply chain partners. From a TCE perspective, transaction costs increase with the number of interfaces that must be managed, monitored, and coordinated (Bode and Wagner, 2015; Williamson, 1985). This increases the effort required for partner selection, contract negotiation, and compliance monitoring—all of which incur significant ex-ante and ex-post transaction costs (Choi and Krause, 2006; Subramani and Agarwal, 2013). From a contract theory perspective, an increase in the number of direct supply chain partners also amplifies contractual incompleteness, leading to higher renegotiation costs and increased risks of opportunistic behavior (Wathne and Heide, 2000). More downstream partners (e.g., distributors and customers) often lead to higher transaction costs in demand forecasting, order processing, and account management. This horizontal complexity not only amplifies the transaction costs but also heightens the risks of disputes and opportunistic behavior, particularly in managing the material and information flows. For instance, managing accurate inventory information and reconciling order statuses across more suppliers and retailers can be challenging. Resolving disputes and preventing potential opportunistic behavior regarding order quantities, specifications, and quality can also be more cumbersome and time-consuming, making the establishment of long-term relationships with multiple partners more difficult.

By automating and streamlining processes through smart contracts, some of these transaction costs and risks can be reduced, especially benefiting firms engaging with a greater number of suppliers. Smart contracts can help minimize transaction costs by automating the routine tasks and facilitating seamless information sharing (Chod and Lyandres, 2023). For example, dynamic pricing algorithms can be coded based on demand and supply conditions instead of extensive negotiations (Song et al., 2021). Moreover, smart contracts contribute to lower firm risks by ensuring that all parties adhere to agreed-upon terms without the need for intermediaries. Payment releases are automated if prespecified conditions are met, minimizing the risks of non-compliance or disputes (Lumineau et al., 2021). Additionally, the transparent and immutable nature of blockchain technology, on which smart contracts are built, reduces the chances of fraud or manipulation. The transparency offered by smart contracts ensures all parties are treated fairly and equitably, and allows them to verify the status of transactions in real time, thus reducing the need for personal trust while enhancing the system trust among supply chain partners (Schmidt and Wagner, 2019). These benefits could be particularly salient for firms with greater horizontal complexity, where the associated transaction costs, the potential for firm risks, and the necessity of trust for maintaining long-term relationships are higher. Consequently, firms with greater horizontal complexity tend to benefit more from smart contract adoption due to the larger potential for transaction cost reductions. Thus, we propose the following hypothesis:

*H2: The positive impact of smart contracts on operational efficiency is more pronounced for firms with greater* *horizontal supply chain complexity.*

**2.3.2 Spatial Complexity**

Greater spatial complexity is associated with greater geographic dispersion of supply chain partners (Bode and Wagner, 2015). In our context, we focus on dispersion across countries, where higher spatial complexity implies greater global sourcing intensity. Compared to domestic markets, global markets are less transparent possibly due to trade restrictions, customs barriers, exchange fluctuations, and institutional differences (Melitz, 2008; Dhingra et al., 2023). From a contract theory perspective, greater spatial complexity exacerbates contractual incompleteness, as firms face increased challenges in aligning agreements across diverse regulatory environments (Segal, 1999). Although smart contracts can be especially beneficial for enhancing transparency and reducing transaction costs in global supply chains, greater spatial complexity may introduce substantial implementation challenges which hinder the full realization of these benefits.

Compliance with country-specific regulations adds significant challenges when implementing smart contracts (Ganne, 2018; Sinha et al., 2022). For instance, the data localization laws in some countries restrict cross-border data flows even on blockchain networks. Countries such as Russia and China have requirements to store citizen data on servers physically located within their own national borders (Newton, 2018). The General Data Protection Regulation (GDPR) in the EU has restrictions on transferring personal data outside the EU (GDPR, 2023). Firms dealing with suppliers operating in these countries with stringent data localization laws face additional challenges and must implement adequate safeguards to ensure compliance. Additionally, intellectual property protections may be weaker on public blockchain networks spanning across borders. Keeping smart contracts up-to-date with dynamic policies and regulatory changes across countries is challenging with decentralized control (Ferreira, 2021). The potential for outdated or non-compliant contracts increases transaction risks. Moreover, while the governments in some countries such as the US, France and China are taking initiatives to recognize the legal validity of smart contracts and financial instruments issued on the blockchain, the legal status of blockchain transactions and smart contracts remains uncertain in many other countries, which complicates cross-border operations (Ganne, 2018). The lack of legal recognition can undermine the wide adoption among supply chain partners, as supply chain partners may be hesitant to fully commit to smart contracts when legal frameworks are inconsistent or unclear.

In summary, from a TCE perspective, the lack of unified regulations and restrictions imposed by some countries on cross-border data flows, taxation, privacy, and blockchain technology implies greater environmental uncertainties, which can limit the global deployment of blockchain-based smart contracts (Ferreira, 2021). Therefore, the effect of smart contract adoption can be compromised for firms with greater spatial supply chain complexity. We thus propose the following hypothesis:

*H3: The positive impact of smart contracts on operational efficiency is less pronounced for firms with greater spatial supply chain complexity.*

**2.3.3 Interconnected Complexity**

Greater interconnected complexity is associated with a greater level of interactions among a firm’s supply chain partners, meaning they are closely linked and dependent on each other for exchange of physical goods, information, and operational processes (Choi and Krause, 2006; Bellamy et al., 2014). Network interconnectedness can create both opportunities and challenges. Such interconnectedness can reduce certain transaction costs by fostering collaborations and resource sharing for better coordination of product specification, production quantity, and delivery time (Choi and Krause, 2006). An example is Toyota’s supplier association, *kyoryoku kai,* which facilitates members to work in a collaborative manner and diffuses Toyota’s best practices throughout the supply chain (Hines, 2016). In highly interconnected supply chains, the transaction costs may already be low due to the close ties and frequent interactions among partners. As a result, the potential benefits of smart contracts in further reducing the transaction costs can be limited. However, the same interconnectedness can also lead to greater firm risks due to the increased likelihood of collusion and opportunistic behavior among partners (Choi and Krause, 2006; Bellamy et al., 2014), particularly vulnerable to contractual incompleteness. For example, informal agreements and verbal commitments often supplement formal contracts, leading to ambiguities and potential opportunistic behavior. Smart contracts, by automating agreements and ensuring precise enforcement, can mitigate contractual incompleteness and reduce risks of disputes. Therefore, while smart contracts might be less beneficial in terms of reducing transaction costs in highly interconnected supply chains, they could be crucial in reducing firm risks. Overall, the effect on operational efficiency can be ambiguous as it depends on the dominance of transaction costs versus firm risks in a supply chain.

While the interconnected complexity’s moderation effect remains unclear based on the above discussions, it is likely to be positive from the perspective of implementation feasibility. Specifically, when supply chain partners are highly interconnected, the reliable and trustworthy collaborations already in place reduce the barriers of adopting smart contracts. These partners are more likely to support and adapt to the implementation of smart contracts, demonstrating the role of trust in lowering transaction costs and enabling smoother cooperation. For example, Bellamy et al. (2014) find that interconnected supply networks strengthen the beneficial impact of supply network accessibility on innovation output, possibly due to the extensive collaborations among supply network partners. Similarly, we expect the benefits of smart contracts in improving operational efficiency to be more readily realized in highly interconnected environments. Therefore, we hypothesize that

*H4: The positive impact of smart contracts on operational efficiency is more pronounced for firms with greater interconnected supply chain complexity.*

**3. Research Methods**

**3.1 Overall Research Design**

We adopt the following steps to test our proposed hypotheses regarding the impact of smart contracts on operational efficiency (H1) and the moderating effects of supply chain complexity (H2 to H4). First, we rely on the enactment of state-level smart contract laws to identify treatment firms. Specifically, we view firms located in states with smart contract laws as treatment firms as these firms should be more likely to adopt and use smart contracts after their states enacted smart contract laws (Chen et al., 2023). We then apply the MDM approach (Ginglinger and Moreau, 2023) to match each treatment firm to a control firm located in a state without smart contract legislation but whose firm characteristics are similar to those of the treatment firm. After identifying treatment firms and matched control firms, we perform DID estimation to compare the change in operational efficiency between treatment and matched control firms from pre- to post-treatment periods, providing a direct test of H1. We then add the interaction effects of supply chain complexity to the DID model for testing H2 to H4. We provide more detailed explanations of these steps in the following sections.

**3.2 Smart Contract Laws**

Based on information from the National Conference of State Legislatures’ (NCSL) state bill tracking database, Arizona was the first state to pass smart contract-related legislation. Specifically, Arizona introduced a legislative bill (bill number: HB 2417) on February 7th 2017 to recognize smart contracts for commercial use. The bill was enacted on March 29th 2017. Following Arizona, several other states such as Tennessee and Arkansas also introduced and enacted smart contract laws.

In essence, these state-level smart contract laws aim to promote the adoption of smart contracts among firms located in their states. The legislative bills reduce legal ambiguity and future disputes regarding smart contract adoption in business transactions by recognizing their applicability in business and providing vital clarity about this technology (Ferreira et al., 2021; Osmani et al., 2021). By doing so, the laws serve as state-backed acknowledgements, which could intrinsically enhance the trust of firms that are ambivalent towards the technology. This can lead to more widespread adoption of smart contracts in these states. As a result, it is reasonable to expect that state-level smart contract laws increase in-state firms’ propensity to adopt and use smart contracts, when compared with out-of-state firms whose states have not enacted similar smart contract laws. Our post hoc analyses in section 4.3 also show that these laws have a positive impact on in-state firms’ smart contract activities in terms of adopting smart contracts and recruiting smart contract talents, providing empirical support to this argument.

We search the NCSL state bill tracking database to identify state-level smart contract laws. First, we compile all state-level blockchain legislation bills from the database. We then carefully review both the summaries and full texts of these bills, with a specific focus on smart contracts. Subsequently, we only retain those bills with provisions explicitly designed to recognize and legitimize smart contracts as commercial contracts, which can be used in commerce and transactions. For example, as Wyoming Senate Bill (bill number: SF 0125) merely describes what a smart contract is and what it can do, without advocating for its use in a commercial setting, we do not include it in this research. Then, we focus on smart contract laws introduced and enacted up to 2019 (i.e., 2017-2019) to avoid possible confounding effects caused by the COVID-19 pandemic that occurred in 2020. Also, as it may take time for smart contract laws to have an impact on firms’ operational efficiency, focusing on smart contract laws introduced in recent years (i.e., from 2020) may fail to detect such an impact. Over the three-year period from 2017 to 2019, we identify a total of six smart contract bills enacted by five different states, namely Arizona, Tennessee, South Dakota, Arkansas, and North Dakota. Online Appendix 1 summarizes these bills, including their exact introduction and enactment dates.

As smart contract laws are implemented at the state level and applied uniformly to all firms operating within those states, individual firms might not have sufficient motivation or influence to drive the enactment of these laws. As such, the smart contract laws are a plausible exogenous shock, facilitating a valid quasi-natural experimental design, as further explained in the following sections. However, some counterarguments may challenge this exogenous assumption. First, firms that expect smart contract laws to help improve operational efficiency may lobby their state governments to pass these laws. If this were the case, our research design would be compromised because the enactment of smart contract laws would no longer be random but instead driven by characteristics of the treatment firms. This may also raise a related reverse causality concern that the enactment of smart contract laws would be influenced by firms’ operational efficiency.

Moreover, although only five states have enacted smart contract laws, firms in other states that are next to those five states may benefit indirectly due to their transaction activities with firms located in the five treatment states. Our research design may hence violate the stable unit treatment value assumption (SUTVA), which requires the absence of spillover effects between treatment and control firms (Chung et al., 2024). Finally, it is possible that smart contract legislation is just one of the corresponding state government’s digital initiatives, suggesting that any operational efficiency improvement observed in our research may be driven by those initiatives rather than by the enactment of smart contract legislation. To address these concerns, we conduct several additional tests and document the results in the Online Appendices 2 to 5. Overall, these test results demonstrate the exclusion restriction of smart contract legislation in our research context and provide empirical support for our quasi-natural experimental research design.

**3.3** **Mahalanobis Distance Matching**

Although firms located outside the five states mentioned above can be viewed as control firms as their states have not enacted smart contract laws, there is an important concern that out-of-state firms’ characteristics (e.g., firm size) may be significantly different from in-state firms’. If this is the case, the observed difference in operational efficiency changes (if any) between in-state and out-of-state firms may be attributed to their different characteristics rather than due to the enactment of smart contract laws.

To address this concern, we adopt the MDM approach (Ginglinger and Moreau, 2023) to match each in-state treatment firm to an out-of-state control firm with similar characteristics. In line with prior research (e.g., Barber and Lyon, 1996; Swift et al., 2019), our matching focuses on three critical firm characteristics including industry type, firm size, and firm profitability. This is because firms’ propensities to adopt smart contracts may vary across different industries. Also, large and profitable firms may have more resources and experiences to support their smart contract adoption compared with small and unprofitable firms. In addition to these three firm characteristics emphasized in the literature, we also include operational efficiency in the MDM as our research investigates the impact of smart contract laws on firms’ operational efficiency. It thus is important to ensure that control firms’ operational efficiency is similar to that of treatment firms before the enactment of the smart contract laws.

To identify the treatment firms, we first search for the headquarters locations of all publicly traded firms in the Compustat database. We determine a firm’s location based on its headquarters because smart contract adoption should be a strategic decision by a firm’s top management team rather than an operational decision by its frontline employees. Therefore, the use of headquarters location, where a firm’s top management team is usually based, is more likely to capture the firm’s decision to adopt smart contracts. This identification approach is also consistent with prior studies that determine treatment firms based on headquarters locations (e.g., Lin et al., 2021; Chen et al., 2023). Through this screening process, we identify 312 treatment firms with confirmed headquarters in the five states that have enacted smart contract legislation.

Next, we construct a control candidate pool including out-of-state firms whose industries (two-digit SIC codes) are the same as in-state treatment firms’. We then adopt the MDM approach to select firms from the control candidate pool based on firm size (total sales), firm profitability (return on assets), and operational efficiency (based on stochastic frontier analysis, further explained below). We obtain the annual accounting data from Compustat to measure these three variables and average each of them over a five-year period preceding the enactment of smart contract laws. This helps ensure that the treatment and matched control firms have similar characteristics over the whole pre-treatment period, not just in the year before the treatment. Firms with missing data for these matching variables (i.e., firm size, firm profitability, operational efficiency) are excluded, resulting in 141 treatment firms for matching. In line with prior research (Chu et al., 2018; Liu and Nguyen, 2023), we perform a one-to-one matching with replacement and use 0.05 as the caliber value, resulting in a total of 242 sample firms, including 124 treatment firms and 118 matched control firms for this study.

We then check possible sampling bias as our sample size is reduced across different steps as described above due to missing data. Specifically, we first compare the differences between firms with and without headquarters information, and could not find significant differences across a list of common firm-level variables such as sales, total assets, market value, and the cost of goods sold (*p* > 0.1; not tabulated). Our one-way ANOVA test results also suggest that the treatment firms in different steps have similar characteristics in terms of those common firm-level variables (*p* > 0.1; not tabulated), providing no evidence of sampling bias. We also conduct several tests to check and confirm the quality of our matching approach, with the test results documented in Online Appendix 6.

**3.4 Difference-in-Differences Estimation**

After identifying treatment and matched control firms, we first construct a baseline DID model, as shown in Equation (1), to estimate the impact of smart contract laws on firms’ operational efficiency and test H1.

where the subscripts *i* and *t* refer to firm and year , respectively. and indicate the firm and year fixed effects, respectively. represents the error terms. is a vector of control variables that may be related to a firm’s operational efficiency. Specifically, we control six firm-level variables, including firm profitability, firm size, firm leverage, cash intensity, tangible assets, and labor intensity. The reason is that, profitable firms, large firms, and firms holding more cashes may have more resources to improve operational efficiency, but highly leveraged firms, firms holding more tangible assets, and labor-intensive firms may face more constraints in efficiency improvement (Lam et al., 2016; Li et al., 2022; Swink and Jacobs, 2012). The three dimensions of supply chain complexity (i.e., horizontal complexity, spatial complexity, and interconnected complexity) are also included as prior research suggests that the complexity of a firm’s supply chains has important implications for firm performance (Bode and Wagner, 2015; Bellamy et al., 2014). The detailed measurements of these variables are shown in Table 1.

--- Table 1 about here ---

The dependent variable included in Equation (1) is, measured based on stochastic frontier analysis (SFA). We choose this measurement approach because SFA can help to model the complex relationships between a firm’s output and different operational inputs, providing a more comprehensive measure of the firm’s operational efficiency (Li et al., 2010). Moreover, the SFA approach computes a firm’s operational efficiency relative to the most efficient firm in the same industry, making the measures comparable across industries (Lam et al., 2016). This is an important consideration in our research that includes sample firms from different industries. Nevertheless, we also measure operational efficiency alternatively based on traditional efficiency ratios and obtain consistent test results, as shown in section 4.1.

Empirically, we follow prior studies (e.g., Li et al., 2010; Li et al., 2022) to model the relationships between a firm’s operational inputs, including number of employees (EMP), cost of goods sold (COGS), and capital expenditure (CEX), and its operational output, which is operating income (OI). To capture the complex relationships among these variables, our model considers not only the linear and nonlinear effects of individual operational inputs but also the interactions among them, as shown in Equation (2).

where the subscripts *i*, *j*, and *t* refer to firm *i*, industry *j* (two-digit SIC code), year *t*, respectively. is the stochastic random error, while represents firm *i*’s technical inefficiency compared to the most efficient firm (i.e., the frontier) in the same industry *j* and year *t*. is in the range of 0 to 1, with a higher value indicating a less efficient firm. We thus use to provide a direct measure of a firm’s operational efficiency.

in Equation (1) is a dummy variable, coded 1 for treatment firms and 0 for matched control firms. is also a dummy variable, coded 1 for the post-treatment period and 0 for the pre-treatment period. The interaction term, , indicates the change of treatment firms’ operational efficiency from the pre-treatment period to the post-treatment period, after controlling for matched control firms’ operational efficiency change over the same period. Therefore, we rely on in Equation (1) to determine the impact of smart contract laws on operational efficiency and test H1. It should be noted that as we have included firm and year fixed effects in the DID model, the individual and terms are dropped from the model due to multicollinearity.

We use five years for both the pre- and post-treatment periods, indicating that our investigation period spans from five years before to five years after the enactment of smart contract laws, explicitly excluding the enactment year. As the implementation of smart contract laws is a complex process and firms may require additional time to assimilate and adopt smart contracts, the effects may not be immediately discernible. Accordingly, a five-year post-treatment period allows us to more comprehensively capture the impact of smart contracts on operational efficiency, providing sufficient temporal scope to observe any delayed effects. Furthermore, the inclusion of a five-year period preceding the enactment of smart contract laws furnishes an adequate pre-shock benchmark.

After testing the impact of smart contract laws on firms’ operational efficiency (H1), we interact the three dimensions of supply chain complexity (i.e., horizontal complexity, spatial complexity, and interconnected complexity) with for testing H2 to H4, as shown in Equation (3).

indicate the firm *i*’s horizontal supply chain complexity in year *t*. We obtain our sample firms’ supply chain relationship data from FactSet Revere, which covers more than 31,000 public firms around the world, comprising over 450,000 business relationships (FactSet, 2021). We then measure a sample firm’s horizontal complexity as its number of first-tier suppliers and customers in each year (Bode and Wagner, 2015; Lu and Shang, 2017). As a robustness check, we also measure upstream horizontal complexity and downstream horizontal complexity separately and document the test results in section 4.2. The interaction between and captures the moderating role of horizontal supply chain complexity. We thus rely on in Equation (3) to test H2.

indicates firm *i*’s spatial supply chain complexity in year *t*, which is the geographic distribution of the firm’s supply chain partners (including first-tier suppliers and customers) across different countries (Lu and Shang, 2017). With the supply chain relationship data obtained from FactSet Revere, we measure spatial complexity based on the Herfindahl index (Kovach et al., 2015). Specifically, we first divide a sample firm’s number of supply chain partners in each country by its total number of supply chain partners to obtain a ratio for each country and then add the squares of these ratios together to represent the Herfindahl index for this firm. The Herfindahl index ranges from 0 to 1, with a higher value indicating a more geographically concentrated supply chain. We thus apply 1 – the Herfindahl index to provide a direct measure of a firm’s spatial supply chain complexity, as shown in Equation (4). We also decompose the measure into upstream spatial complexity and downstream spatial complexity and conduct robustness tests in section 4.2. The interaction between and captures the moderating role of spatial supply chain complexity. We thus rely on in Equation (3) to test H3.

where *Pk* represents the proportion of a firm’s supply chain partners (including first-tier suppliers and customers) located in country *k*.

indicates firm *i*’s interconnected supply chain complexity in year *t*. With supply chain relationship data obtained from FactSet Revere, we follow Bellamy et al. (2014) and measure interconnected complexity as one minus the network efficiency index proposed by Burt (1992), as shown in Equation (5). Burt (1992)’s network efficiency index typically measures the efficiency of a network, with a higher value indicating a more efficient and less redundant network. In other words, a high network efficiency index suggests that a firm’s supply chain partners have more direct connections and fewer redundant ties. By subtracting this index from 1, higher values in our measurement correspond to less efficient networks with more densely connected supply chain partners and greater redundancy ties, reflecting higher interconnected complexity. We also decompose the measure into upstream interconnected complexity and downstream interconnected complexity in the robustness tests documented in section 4.2. The interaction between and captures the moderating role of interconnected supply chain complexity. We thus rely on in Equation (3) to test H4.

where is the proportion of firm *i’*s ties invested in the relationship with *q*,is the marginal strength of the tie between members *j* and *q* (who are both directly connected to firm *i*), and is the total number of direct partners of firm *i*. The connection representations are binary, with the values of ​ are set to 1 if a tie is present between members *j* and *q*, and 0 otherwise.

We adopt a two-way fixed effects estimator for our staggered DID model which is a common approach for estimating causal inference in prior OM studies (e.g., Barker et al., 2022; Elenev et al., 2024). We also supplement our main analysis with a Tobit regression model (Shen et al., 2023) and obtain consistent test results, as further discussed in section 4.1.

**4. Test Results**

**4.1 The Impact of Smart Contracts on Operational Efficiency**

After eliminating missing values, the full sample for the DID analysis comprises 1,599 firm-year observations, representing 242 firms over the period of 2012–2022. Table 2 shows the correlations and descriptive statistics of all variables included in the DID model. Table 3 displays the test results of the baseline DID analysis with operational efficiency as the dependent variable. Specifically, Model 1 in Table 3 represents the results of the baseline DID model, while Models 2 to 8 document the results of various robustness tests based on the baseline DID model. The *F*-tests suggest that all models are significant (*p* < 0.01), with *R*-squared values ranging between 0.038 and 0.073. It should be noted that firm- and year-fixed effects account for any firm-invariant (e.g., *Treatment*) and time-invariant (e.g., *Post*) factors. Consequently, the main effects of *Treatment* and *Post* are absorbed by the two-way fixed effects and are omitted in all models. The results of the baseline DID model are used to test H1. As shown in Model 1 of Table 3, the coefficient of *Treatment × Post* is positive and significant (*p* < 0.05), suggesting that the operational efficiency of the treatment firms improves from the pre-treatment period to the post-treatment period, after controlling for the change in operational efficiency of the matched control firms over the same period. This indicates a positive effect of smart contracts on firms’ operational efficiency, supporting H1.

--- Table 2 and 3 about here ---

We further conduct several tests with alternative estimation, measurement and matching approaches, to check the robustness of our findings and document the test results in Models 2 to 8 of Table 3. Overall, these robustness checks show consistent results, suggesting that smart contracts have a positive impact on firms’ operational efficiency. In the following, we provide detailed explanations of these tests.

We first follow Roth et al. (2023) and perform additional robustness tests on our staggered DID model based on different estimation methods. Specifically, we begin by performing the heterogeneity-robust estimation of the DID model, obtaining consistent test results showing a significant and positive effect of smart contracts on operational efficiency (*b* = 0.013, *p* < 0.01). Additionally, Roth et al. (2023) suggest applying cluster-robust methods when there are a large number of treated and untreated clusters sampled from a super-population. Following this recommendation, we apply cluster-robust standard errors at the state level when estimating our DID model. The results, presented in Model 2 of Table 3, consistently demonstrate the positive impact of smart contracts on operational efficiency (*p* < 0.05).

As we apply SFA to measure operational efficiency and then use it as the dependent variable in our DID model, it raises the concern that this two-step approach may affect the standard errors and coefficients in the DID estimation. Specifically, the SFA-estimated operational efficiency measures are not directly observed firm outcomes but derived from a regression model. In this way, the estimation variability in SFA could influence the standard errors and coefficient estimates in the second-stage DID model. To address this concern, we follow prior studies (e.g., Allon et al., 2023; Xu et al., 2023) and perform a bootstrapped analysis in the DID estimation. The bootstrapping approach can adjust standard errors in the DID model and account for variability introduced by the first-stage SFA estimation. While such approach does not fully resolve model interdependencies and estimation variability, it still provides important evidence that the use of the SFA approach does not bias our main findings, as shown in Model 3 of Table 3.

To further address this concern, we employ alternative measures of operational efficiency based on non-SFA approaches. Specifically, we follow prior OM research (e.g., Hu et al., 2023; Lu and Shang, 2017) and measure operational efficiency alternatively as the ratio of sales to inventory and the ratio of sales to property, plant, and equipment (PPE), respectively. We then rerun the DID model with these two alternative measures as the dependent variable, obtaining consistent test results as shown in Models 4 and 5 of Table 3.

In addition, given that our dependent variable (i.e., operational efficiency) based on the SFA measurement approach is truncated between 0 and 1, this constraint results in censoring and may bias the two-way fixed effects estimation in our DID model. To address this concern, we supplement our main analysis with a Tobit regression model (Shen et al., 2023) and obtain consistent test results, as documented in Model 6 of Table 3. Model 7 of Table 3 further suggests that our test results remain qualitatively similar if we conduct the random effects estimation, in which the firm and year fixed effects are not included.

Moreover, we adopt an alternative approach to identify the treatment firms based on employee locations rather than headquarters locations to better account for firms’ operational footprints. We first collect firm-level employment data from Revelio Labs that compiles and standardizes employee profiles and geographic employment distributions for US-listed firms (Baker et al., 2024). This dataset thus enables us to determine whether a firm operates in a treatment state based on its employee locations. Specifically, we consider a US-listed firm as a treatment firm if at least 5% of its employees[[3]](#footnote-3) were in a treatment state when the smart contract law was enacted. After removing firms without data for measuring our research variables, we obtain 496 treatment firms and then apply the same MDM approach to match these treatment firms to control firms. The final sample after matching consists of 824 firms (including 433 treatment firms and 391 matched control firms), which are used for the DID analysis. The test results based on this alternative identification approach remain consistent, as documented in Model 8 of Table 3.

Lastly, we examine whether our findings are sensitive to different matching approaches and alternative estimation periods, obtaining consistent test results in Online Appendix 7. We also perform a placebo test in Online Appendix 8 to check and confirm that our test results are not driven by other unobservable factors than the enactment of smart contract laws.

**4.2 The Moderating Effects of Supply Chain Complexity**

After demonstrating the positive impact of smart contracts on operational efficiency and providing solid support for H1, we further investigate the moderating effects of supply chain complexity and test H2 to H4. The test results by running Equation (3) are documented in Table 4, with the moderating effects of horizontal complexity (H2), spatial complexity (H3), and interconnected complexity (H4) being incorporated into Models 1, 2, and 3, respectively. We then incorporate all three-way interaction terms into Model 4 of Table 4. The maximum and mean VIF values for Model 4 are 2.03 and 1.06, respectively, both well below the commonly accepted threshold of 10 (Anand et al., 2021), indicating that multicollinearity is not a significant concern in our research. The *F*-tests suggest that all four models are significant (*p* < 0.001), with *R*-squared values ranging between 0.072 and 0.083.

We use the test results from Model 4 (i.e., the full model) to evaluate our hypotheses. The interaction between *Treatment × Post* and *Horizontal Complexity* is positive and significant (*p* < 0.001), suggesting that horizontal complexity positively moderates the relationship between smart contracts and operational efficiency. The finding supports H2. By contrast, there is a negative and significant interaction between *Treatment × Post* and *Spatial Complexity* (*p* < 0.05), demonstrating a negative moderating role of spatial complexity and supporting H3. Lastly, the interaction between *Treatment × Post* and *Interconnected Complexity* is positive but not significant (*p* > 0.1), indicating that interconnected complexity does not moderate the impact of smart contracts on operational efficiency. Thus, H4 is rejected. This non-significant result may be due to the trade-off between the uncertainty associated with smart contract adoption and the opportunity for transaction cost reduction embedded in interconnected supply chain complexity (Choi and Krause, 2006; Bellamy et al., 2014). Specifically, although it is easier to adopt smart contracts in a highly interconnected supply chain to reap efficiency benefits, such a supply chain exhibits lower ex ante transaction costs, providing fewer opportunities for firms to adopt smart contracts to reap efficiency benefits.

--- Table 4 about here ---

We then further explore whether the moderating effects of supply chain complexity differ between the upstream and downstream sides. Specifically, we decompose the full supply chain complexity into upstream and downstream supply chain complexity (Bode and Wagner, 2015; Bozarth et al., 2009). Upstream supply chain complexity is concerned with the complexity of a firm’s supplier base such as the number of suppliers (upstream horizontal complexity), the distribution of suppliers across countries (upstream spatial complexity), and the interconnected relationships between suppliers (upstream interconnected complexity). In contrast, downstream supply chain complexity focuses on the complexity of a firm’s customer base, such as the number of customers (downstream horizontal complexity), the distribution of customers across countries (downstream spatial complexity), and the interconnected relationships between customers (downstream interconnected complexity).

We rerun Equation (3) for upstream supply chain complexity and downstream supply chain complexity separately, resulting in Models 5 and 6, respectively, in Table 4. The directions of coefficients remain consistent across the two models. However, the moderating effect of spatial complexity is more negative in downstream supply chains than upstream supply chains. This finding suggests that firms benefit less from smart contracts when they are serving customers (rather than sourcing from suppliers) located in different countries. This finding may be explained by the power asymmetry in buyer-supplier relationships (Chae et al., 2017; Sutton-Brady et al., 2015): as customers are usually more powerful than suppliers in a typical supply chain, it may be more difficult and challenging for a firm to force its overseas customers (rather than overseas suppliers) to adopt smart contracts, preventing the firm from reaping smart contracts’ benefits.

In summary, our test results suggest that the impact of smart contracts on operational efficiency differs across firms depending on different dimensions of supply chain complexity. Specifically, firms with a large number of supply chain partners (i.e., high horizontal complexity) experience better operational efficiency improvement arising from smart contracts. By contrast, the operational efficiency improvement is less pronounced for firms whose supply chain partners are distributed across different countries (i.e., high spatial complexity). Finally, the operational efficiency improvement is independent of whether firms’ supply chain partners are closely connected to each other (i.e., high interconnected complexity).

**4.3 Post Hoc Analyses**

We conducted several post hoc analyses to address important questions arising from our finding regarding the positive impact of smart contracts on firms’ operational efficiency. Specifically, our post hoc analyses examine: (1) the channels through which smart contracts improve operational efficiency, (2) whether the enactment of state-level smart contract laws promotes more smart contract activities for in-state firms, and (3) how the effects of smart contracts on operational efficiency change over time and vary across industries.

**4.3.1 Channel Testing**

In line with our theoretical explanations provided in the hypothesis development, we collect additional secondary data and follow previous studies (e.g., Brown and Huang, 2020; Lai et al., 2025) to test the channels (i.e., cost reduction, risk mitigation, and relationship enhancement) through which smart contracts lead to operational efficiency improvement. The test results are documented in Table 5 and further explained below.

--- Table 5 about here ---

First, for cost reduction, we examine the impact of smart contracts on firms’ total operating costs, commonly measured as operating expenses in the OM literature (Zhang et al., 2013). We focus on total operating costs because TCE suggests that “organizations will choose the business alternative that yields the lowest total cost of running their operations” (Ellram et al., 2008, p. 149). We rerun the DID model with firms’ operating expenses obtained from Compustat as the dependent variable. The test results, presented in Model 1 of Table 5, show that smart contracts do have a significant and negative impact on firms’ operating costs (*p* < 0.001), consistent with our cost reduction explanation.

We then further investigate how smart contracts may affect different types of firm cost (e.g., production cost, sales cost, inventory cost, and labor cost) to gain a deeper understanding of the cost reduction capability of smart contracts. Following prior studies (e.g., Fan and Liu, 2017; Liang et al., 2023; Liu and Zhang, 2024; Chang et al., 2024), we obtain Compustat data and measure a firm’s production cost as the cost of goods sold (COGS), sales cost as selling, general, and administrative (SG&A) expense, inventory cost as the monetary value of total inventories, and labor cost as the wages and salaries of employees. The DID test results, documented in Models 2 to 5 of Table 5, suggest that smart contracts help reduce firms’ costs related to production, sales, and inventory activities (*p* < 0.05), but smart contracts do not have a significant impact on their labor costs (*p* > 0.1). This may be because although smart contracts help automate certain processes (Olsen and Tomlin, 2020), which should reduce labor costs, the use of smart contracts may require firms to recruit smart contract talents, as shown in section 4.3.2, which will increase labor costs. As a result, smart contracts’ overall impact on labor costs is unclear.

Regarding risk mitigation, we investigate the impact of smart contracts on a firm’s overall risk, measured as the firm’s annualized standard deviation of monthly stock returns (Dewan and Ren, 2011). We consider overall firm risk because smart contracts may affect different types of firm risk such as opportunism risk and asset-specific investment risk, as discussed in the hypothesis development. The test results, documented in Model 6 of Table 5, show that while the impact of smart contracts on overall firm risk is negative, it is not statistically significant (*p* > 0.1). We also measure overall firm risk alternatively as a firm’s annualized standard deviation of daily (instead of monthly) stock returns (Li et al., 2022) but still obtain non-significant test results (*p* > 0.1), as shown in Model 7 of Table 5.

Finally, regarding relationship enhancement, we examine the impact of smart contracts on the stability of a firm’s relationships with supply chain partners, which indicates the extent to which the firm’s supply chain partners remain unchanged over time (Ostrovsky, 2008). Specifically, we obtain supply chain relationship data from FactSet Revere and measure *Relationship Stability* for each sample firm in year *t* as the number of suppliers and customers that remain unchanged from years *t-1* to *t* divided by the sample firm’s total number of suppliers and customers in year *t*. It should be noted that if a sample firm drops one supply chain partner and adds another, we consider this as a change in two supply chain partners rather than a zero change. We then rerun the DID model with *Relationship Stability* as the dependent variable. The test results, documented in Model 8 of Table 5, suggest that smart contracts help improve the stability of a firm’s relationships with supply chain partners (*p* < 0.05).

Taken together, our results indicate that smart contracts are more likely to improve operational efficiency through cost reduction and relationship enhancement than risk mitigation. Specifically, smart contracts help firms reduce costs related to overall operations, production, sales, and inventory activities, but also enhance firms’ relationships with supply chain partners, ultimately leading to operational efficiency improvement.

**4.3.2 Smart Contract Laws, Smart Contract Activities, and Operational Efficiency**

Our quasi-natural experimental design is based on the key premise that the enactment of state-level smart contract laws should increase the propensity of in-state firms to adopt and use smart contracts. Therefore, it is reasonable to question whether firms’ smart contract activities actually increased after their states passed such laws. To address this concern, we collect additional data and conduct further analyses to assess the impact of smart contract laws on firms’ actual smart contract activities, as well as the subsequent effects of these smart contract activities on the firms’ operational efficiency.

We first test the impact of smart contract laws on firms’ smart contract adoption. To determine whether our sample firms[[4]](#footnote-4) (including treatment and control firms) have actually adopted smart contracts, we conduct a comprehensive search for related announcements using “smart contract” and keywords related to smart contract languages (e.g., Solidity, Vyper) and platforms (e.g., Ethereum, Hyperledger Fabric) (Agrawal et al., 2023; Kannengiesser et al., 2021). Our search covers all sample firms’ annual reports, official websites, and business news databases (i.e., Factiva and Google News) from 2012 to 2022. Initially, we retain all announcements that mention these keywords. We then manually review each collected announcement in detail to determine whether the firm mentioned in the announcement has indeed adopted smart contracts. Specifically, during this review, we exclude any announcements that are ambiguous in adoption purpose and lack a specific adoption year. After this thorough screening process, we create a dummy variable named *Smart Contract Adoption* to indicate whether a sample firm adopts smart contracts in a specific year.

We then construct a logit regression model using *Smart Contract Adoption* as the dependent variable, while the independent variables are the same as those included in the DID model. The test results, documented in Models 1 and 2 of Table 6, show that the interaction term *Treatment* × *Post* is positive and significant (*p* < 0.05) for sample firms identified based on headquarters locations and employee locations, respectively. This finding indicates that state-level smart contract laws have a positive impact on in-state treatment firms’ smart contract adoption, after controlling the smart contract adoption of out-of-state control firms.

Additionally, we use the number of smart contract talents in our sample firms (including treatment and control firms) as an alternative measure of firms’ smart contract activities. Here, smart contract talents refer to employees with specific experience and skills related to smart contracts. To identify such talents, we conduct a systematic search on LinkedIn using keywords related to smart contract languages and platforms, such as Solidity, Vyper, Ethereum, and Hyperledger Fabric (Agrawal et al., 2023; Kannengiesser et al., 2021). We manually review each LinkedIn profile in the searched results to determine whether these individuals have working experience at any of our sample firms. We also carefully examine whether the relevant keywords appear in their job titles, responsibilities, and listed skills to ensure that these profiles indeed have the necessary expertise in smart contracts. We retain only the LinkedIn profiles that clearly mention smart contract-related skills and indicate current or previous employment at our sample firms. For each of these retained profiles, we record their employment start and end years at our sample firms. We then create a new variable named *Smart Contract Talent* to indicate the number of employees with smart contract skills in each sample firm in a specific year. We apply log-transformation to the *Smart Contract Talent* variable to account for the potential skewness of values across firms.

We then rerun the DID model from 2012 to 2022 with *Smart Contract Talent* as the dependent variable. The test results, documented in Models 3 and 4 of Table 6, show positive and significant *Treatment × Post* (*p* < 0.05) for sample firms identified based on headquarters locations and employee locations, respectively. This finding suggests that smart contract legislation increases the number of smart contract talents in treatment firms, when compared with that in the matched control firms. Taken together, these tests provide empirical support to our quasi-natural experimental design that relies on the enactment of smart contract laws to study the impact of smart contracts on firms’ operational efficiency.

--- Tables 6 and 7 about here ---

We then further test the impact of firms’ smart contract activities in terms of smart contract adoption and smart contract talents on operational efficiency. We first focus on the impact of smart contract adoption. Our comprehensive searches of annual reports, official websites, and business news databases discussed above have identified eight treatment firms with smart contract adoption for the headquarters location sample and 24 treatment firms with smart contract adoption for the employee location sample. This represents smart contract adoption rates of 6.45% (8/124) and 5.54% (24/433), respectively, which are much higher than the average adoption rate of all US-listed firms[[5]](#footnote-5). The significant difference suggests that firms located in the treatment states with smart contract laws are more likely to adopt smart contracts.

We then conduct a DID analysis to estimate how these firms’ smart contract adoption affects their operational efficiency. Specifically, we match each of the treatment firms with smart contract adoption to a control firm without such adoption in the period of 2012 to 2022. We create a dummy variable, *Smart Contract Adoption*, to indicate whether a firm is a treatment firm (coded 1) or a matched control firm (coded 0). We also create another dummy variable, *Post Adoption*, to indicate whether a specific year is before (coded 0) or after (coded 1) the smart contract adoption. The DID test results, with *Operational Efficiency* as the dependent variable, are presented in Models 1 and 2 of Table 7 for sample firms identified based on headquarters locations and employee locations, respectively. The finding suggests that treatment firms’ operational efficiency increases significantly from pre- to post-adoption periods, after controlling the efficiency changes of matched control firms over the same periods (*p* < 0.05).

We also test the relationship between a firm’s number of smart contract talents and its operational efficiency. As *Smart Contract Talent*, measured based on LinkedIn data as discussed above, is a continuous variable, a DID estimation approach is less appropriate. Instead, we directly regress *Operational Efficiency* on *Smart Contract Talent* for sample firms but also include all control variables, firm fixed effects, and year fixed effects in the regression model. The regression test results, presented in Models 3 and 4 of Table 7, show that the coefficient of *Smart Contract Talent* is positive and significant (*p* < 0.05) for sample firms identified based on headquarters locations and employee locations, respectively. This suggests that a firm’s number of smart contract talents is positively related to its operational efficiency. Overall, these test results based on firms’ actual smart contract activities support our main finding that smart contracts indeed play an important role in improving operational efficiency.

**4.3.3 Time and Industry Effects**

Although our research shows that smart contracts have a positive impact on firms’ operational efficiency, it is unclear how smart contracts affect firms’ operational efficiency over time during the post-treatment period, and which industries benefit more from using smart contracts. To answer these questions, we perform additional tests to examine the impact of smart contracts across different post-treatment periods and various industries.

For time-specific effects, we divide the five-year post-treatment period (i.e., years 1 to 5) into three sub-periods, including year 1, years 2 to 3, and years 4 to 5, capturing smart contracts’ short-, medium-, and long-term effects, respectively. We then create three dummy variables to represent the three sub-periods and interact each of them with the *Treatment* variable in the DID model. The test results documented in Model 1 of Table 8 suggest that smart contracts do not have a significant impact on firms’ operational efficiency in the short-term (year 1), but the impact becomes significant (*p* < 0.05) in both the medium-term (years 2 to 3) and long-term (years 4 to 5). Overall, these results suggest that it may take time for smart contracts to have a significant impact on firms’ operational efficiency.

--- Table 8 about here ---

For industry-specific effects, we focus on three industries based on two-digit SIC codes, including Wholesale and Retailing (50-59), Manufacturing and Transportation (20-49), and Services (70-89). We interact each of the three industries with the *Treatment × Post* term in the DID model. The test results documented in Model 2 of Table 8 indicate that while the wholesale and retailing industry reaps slightly more benefits from smart contracts (*p* < 0.1), there is no strong evidence to suggest significant industry-specific effects across different industries. These findings suggest that the benefits of smart contracts may not be confined to specific industries but could be more broadly distributed.

**5. Conclusion and Discussion**

To conclude, by leveraging the passage of state-level smart contract laws in the US, our research shows that in-state treatment firms’ operational efficiency improves significantly compared with that of out-of-state matched control firms. Our test results remain consistent across various robustness checks. We also confirm that state-level smart contract laws do increase the respective in-state firms’ smart contract activities, which in turn lead to operational efficiency improvement. Our additional analysis further uncovers that it may take time for firms to realize the operational efficiency benefits after the enactment of smart contract laws and such benefits are mainly due to cost reduction and relationship enhancement, consistent with our theoretical explanations formulated in the hypothesis development. We also find that the operational efficiency improvement is more pronounced for firms with high horizontal supply chain complexity but low spatial supply chain complexity. Our findings provide important academic and practical implications, as discussed below.

**5.1 Implications for Research**

There is no doubt that blockchain-enabled smart contracts, with their increasing popularity and importance, have attracted significant attention from the research community. While there have been a lot of discussions on the potential risks and benefits of adopting smart contracts (Wang and Xu, 2023; Chod and Lyandres, 2023; Wang et al., 2021; Liu et al., 2023; Chang et al., 2019), limited quantitative research has been conducted to examine the impact of smart contract adoption on firm-level operational outcomes. Our research represents one of the first empirical studies to quantitatively investigate how smart contracts may affect firms’ operational efficiency, providing important implications for future smart contract research. In particular, the lack of relevant quantitative research may be due to the difficulty of collecting smart contract data (i.e., firms seldom disclose their smart contracts and no existing database is available) and the challenge of addressing endogeneity concerns (i.e., the relationship between smart contract adoption and operational outcomes could be endogenous and subject to omitted variable concerns).

Our research overcomes these difficulties and challenges by conducting a quasi-natural experiment in the US based on the enactment of smart contract laws at the state level. Importantly, we have collected additional data and empirically demonstrated that the enactment of state-level smart contract laws does increase in-state firms’ smart contract activities in terms of adopting smart contracts and recruiting smart contract talents. We also conduct additional tests to rule out some alternative explanations regarding the exogeneity of smart contract laws in our research context. Therefore, our research lays a solid empirical foundation for future research to investigate the impact of smart contracts on other operational outcomes. For example, future research can employ our empirical approach to examine the impact of smart contracts on firms’ product quality as smart contracts can be used to automate the tracking and reporting of goods as they move through the supply chain, enabling firms to identify and address product quality issues early in the process (Xu et al., 2021). Our quantitative approach can also be applied to the supply chain-level analysis to quantify how smart contracts affect different supply chain outcomes such as supply chain efficiency and leanness.

In addition to documenting empirical evidence, our research also reveals the channels through which smart contracts affect firms’ operational efficiency. Specifically, we adopt a TCE perspective to argue that smart contracts help improve operational efficiency by reducing transaction costs, mitigating firm risks, and enhancing interfirm relationships. Consistent with our theoretical arguments, our empirical tests suggest that smart contracts do have a negative impact on various costs associated with firms’ operations, production, sales, and inventory activities. We also find that smart contracts help stabilize firms’ relationships with supply chain partners. Interestingly, we find a negative but insignificant impact of smart contracts on overall firm risk. This may be because although smart contracts help reduce certain firm risks such as opportunism risk and asset-specific investment risk (Lumineau et al., 2021; Schmidt and Wagner, 2019), they may induce other new risks for firms such as data privacy and information security risks (Chang et al., 2019), resulting in an unclear impact on firms’ overall risks. We thus encourage future research to further investigate the impact of smart contracts on different types of firm risks, advancing our understanding of the risk implications of adopting smart contracts.

We extend the TCE perspective by considering the role played by supply chain complexity. While complex supply chains that exhibit high ex ante transaction costs may imply a good opportunity for firms to adopt smart contracts to reduce transaction costs and improve operational efficiency, such supply chains may also induce a high level of uncertainty and hence risk for smart contract adoption, making it more challenging for transaction cost reduction and thus operational efficiency improvement. Therefore, supply chain complexity represents an interesting boundary condition that enriches our TCE explanations. This finding highlights the importance of considering the supply chain context in which smart contracts are adopted when studying the operational outcomes of such adoption. The trade-off between the opportunity for transaction cost reduction and the uncertainty associated with smart contract adoption emphasized in our research may serve as a useful theoretical guideline for researchers to select and explain supply chain factors in their smart contract research. For instance, future smart contract research can adopt the trade-off argument to consider and explain the role of buyer-supplier relationships, an important supply chain factor that has been well studied in the literature (Villena et al., 2011). In particular, while good buyer-supplier relationships may reduce the uncertainty of smart contract adoption, such relationships may also imply lower ex ante transaction costs and thus fewer opportunities for transaction cost reduction, which is worth further investigation.

Our research also contributes to the literature on supply chain complexity. Different from prior studies that have generally demonstrated the similar roles played by different dimensions of supply chain complexity (Bode and Wagner, 2015; Bozarth et al., 2009), our research suggests that not all supply chain complexities are the same. In particular, while horizontal supply chain complexity helps enhance the positive impact of smart contracts on operational efficiency, spatial supply chain complexity in fact makes the positive smart contract-operational efficiency relationship less pronounced. Interestingly, the smart contract-operational efficiency relationship is independent of a firm’s interconnected supply chain complexity. Such differences may be due to the fact that prior studies have focused on the direct impact of supply chain complexity (Bode and Wagner, 2015; Bozarth et al., 2009), but our research considers the moderating role of supply chain complexity in the smart contract context. We thus encourage future research to further explore how different dimensions of supply chain complexity may play different (and even opposite) roles in other specific research contexts, revealing new insights and advancing our understanding of the complexity of supply chain complexity.

**5.2 Implications for Practices**

The global smart contract market is expected to reach $2.5 billion by 2032, representing a compound annual growth rate of 30% from 2023 to 2032 (PR Newswire, 2023), but many firms still decline to adopt smart contracts due to various concerns such as data privacy, information security, and adoption costs (Chang et al., 2019). While these concerns should not be overlooked, our research suggests that firms can benefit from smart contract adoption in terms of operational efficiency improvement. In today’s highly competitive environment, superior operational efficiency has important implications for a firm’s sustainable competitive advantage and long-term survival. Therefore, our research encourages firms to embrace smart contracts, leading to operational efficiency improvement.

However, firms should realize that smart contract is not a one-size-fits-all technology, suggesting that the degree of operational efficiency improvement arising from smart contract adoption may depend on the adoption context. In particular, our research shows that firms doing business with a large number of supply chain partners benefit more from smart contract adoption. This finding is in line with some practitioners’ view that smart contracts “could facilitate a lot of supply chain transactions in a positive way” (Gideon, 2023). However, our research also reveals that it is more difficult for firms to reap smart contracts’ benefits if their supply chain partners are located across different countries. Some practitioners also highlight the uncertainties of adopting smart contracts “across borders or incorporate participants from other countries” (Gideon, 2023). Overall, to better inform their smart contract decisions, firms need to pay attention to the supply chain contexts in which smart contracts are adopted and assess whether their supply chains provide opportunities or induce uncertainties for smart contract adoption.

On the other hand, firms should not assume that certain industries will definitely reap more efficiency benefits from smart contract adoption. Although firms in some industries (e.g., information technology) may have more knowledge and experience with blockchain technology and smart contracts, it does not necessarily imply that they will benefit more from adopting smart contracts. Our research also does not find strong industry effects in terms of efficiency improvement due to smart contract adoption. Therefore, we encourage firms across different industries to adopt smart contracts to reap the efficiency benefits rather than to assume that smart contracts may only work in certain industries.

Our research has some direct implications for governments or policymakers. In particular, while our research demonstrates the positive impact of smart contracts on firms’ operational efficiency, providing solid empirical support for the enactment of smart contract laws, we also find that it takes time for firms to realize the benefits arising from the enactment. Specifically, we find that smart contract laws do not have a significantly positive impact on firms’ operational efficiency until two years after the enactment. This finding suggests that governments can do more to “speed up” the positive impact of smart contract laws. For example, as many businesses still have a limited understanding of smart contracts and lack expertise for smart contract adoption (Chang et al., 2019), governments can allocate more resources for smart contract promotion and education, moving beyond just passing the smart contract laws. Moreover, governments may need to take a more global view of smart contract adoption, collaborating with other overseas governments to facilitate a more consistent, supportive international legal environment for smart contract adoption. This is because our research suggests that firms may be unable to capitalize on the enactment of local smart contract laws if they do business with supply chain partners located across different countries. Overall, the enactment of local, state-level smart contract laws should be viewed as the first but not the only step. Much could be done to enable the positive impact of smart contract laws to emerge faster and to become stronger.

**5.3 Limitations and Future Research Directions**

Our study has several limitations which in turn provide new opportunities for future research. First, our research focuses on public-listed firms with headquarters in the US, which may limit the generalizability of our findings to other firms. For example, compared with public-listed firms, private firms, especially small and medium-sized enterprises (SMEs), may be less motivated to adopt smart contracts due to limited resources and lack of expertise. Also, foreign firms with US operations may be affected by the smart contract laws differently as these firms are also subject to home-country regulations and cross-border legal frameworks. Therefore, future research can explore other relevant databases to investigate the implications of smart contracts for other firms that are not covered by our research.

Empirically, our research investigates the enactment of smart contract laws on firms’ operational efficiency. Although this investigation approach overcomes the difficulty of obtaining smart contract data and addresses possible endogeneity concerns (Chen et al., 2023), it gives rise to the question of whether we can interpret the findings as firms’ actual smart contract adoption. We address this concern by collecting additional data and empirically showing that the enactment of smart contract laws does increase firms’ actual smart contract activities, but it should be noted that our sample size is relatively small, which may limit the generalizability of our findings. We thus encourage future research to explore other data sources and/or other measurement approaches, corroborating the findings documented in our research.

Relatedly, our study primarily focuses on the impact of smart contracts but does not explore the motivations behind their adoption or the challenges firms face during implementation. Recent studies have highlighted key barriers to the adoption of blockchain-enabled smart contracts, including technological readiness, regulatory uncertainty, and integration complexities (Dwivedi et al., 2023; Kumar et al., 2020). Therefore, future research could further investigate the factors driving smart contract adoption and examine how firms effectively implement and integrate smart contracts into their operations.

Furthermore, we conduct firm-level analysis in this research, paying less attention to other levels of analysis. Researchers could explore the possibility of accessing other data sources and move beyond the firm-level analysis to reveal new insights about smart contract adoption. For example, with appropriate contract- and transaction-level data, researchers can study the operational implications of adopting smart contracts with different purposes, values, criticalities, and other characteristics. Also, by using supply chain-level smart contract data, researchers can investigate how smart contract adoption diffuses in a supply chain and how such diffusion influences focal firms’ operational efficiency.

Additionally, the way we measure firm risk may limit our ability to fully capture the risk mitigation effects of smart contracts. Specifically, we use the standard deviation of stock returns, which is widely adopted in prior research and primarily reflects financial rather than operational risk. It is possible that smart contracts help reduce operational risks that are not captured by this measure. We therefore suggest that future research consider alternative measures (e.g., supply chain disruptions and delivery delays) more closely aligned with operational risk when suitable secondary data becomes available.

Finally, our research focuses on the moderating role of supply chain complexity, or more specifically, the horizontal, spatial, and interconnected dimensions of supply chain complexity. Although these three dimensions of supply chain complexity are particularly relevant to our research concerned with smart contracts between focal firms and direct supply chain partners, we acknowledge that supply chain complexity is a multi-dimensional concept and other complexity dimensions may also moderate the impact of smart contracts on operational efficiency. For example, eliminative complexity, which is the level of connection between a firm’s direct suppliers and customers, indicates the phenomenon of “supply chain disintermediation” (Lu and Shang, 2017, p. 29). This is in line with the removal of intermediaries enabled by smart contracts (Olsen and Tomlin, 2020). Therefore, we encourage future research to further investigate other dimensions of supply chain complexity and advance our understanding of their roles in the smart contract-operational efficiency relationship.

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**Table 1. Variable Measurements**

|  |  |  |
| --- | --- | --- |
| Variables | Measurements | Data Sources |
| (1) Operational Efficiency | Stochastic frontier analysis that models a firm’s efficiency in converting its operational inputs into operational output. | Compustat |
| (2) Treatment | A dummy variable which is coded as 1 for the treatment firms and 0 for the matched control firms. | NCSL |
| (3) Post | A dummy variable which is coded as 1 for the post-treatment period and 0 for the pre-treatment period. | NCSL |
| (4) Firm Profitability | Operating income divided by total assets. | Compustat |
| (5) Firm Size | The natural logarithm transformation of total sales. | Compustat |
| (6) Firm Leverage | Total debt divided by total assets. | Compustat |
| (7) Cash Intensity | Cash holdings divided by total assets. | Compustat |
| (8) Tangible Assets | Property, plant and equipment divided by total assets. | Compustat |
| (9) Labor Intensity | The number of employees divided by total sales, then multiplied by 1000. | Compustat |
| (10) Horizontal Complexity | The total number of first-tier suppliers and customers. | FactSet Revere |
| (11) Spatial Complexity | 1 minus the Herfindahl Index. This variable represents the geographic distribution of first-tier suppliers and customers across different countries. | FactSet Revere |
| (12) Interconnected Complexity | 1 minus the network efficiency index proposed by Burt (1992). This variable represents the extent to which a firm’s supply chain partners are densely connected. | FactSet Revere |

**Table 2. Correlations and Descriptive Statistics**

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| (1) Operational Efficiency | 1.000 |  |  |  |  |  |  |  |  |  |  |  |
| (2) Treatment | -0.036 | 1.000 |  |  |  |  |  |  |  |  |  |  |
| (3) Post | -0.042† | 0.021 | 1.000 |  |  |  |  |  |  |  |  |  |
| (4) Firm Profitability | 0.016 | 0.041† | 0.027 | 1.000 |  |  |  |  |  |  |  |  |
| (5) Firm Size | -0.089\*\*\* | 0.020 | 0.134\*\*\* | 0.448\*\*\* | 1.000 |  |  |  |  |  |  |  |
| (6) Firm Leverage | -0.074\*\* | -0.004 | 0.080\*\*\* | -0.116\*\*\* | 0.200\*\*\* | 1.000 |  |  |  |  |  |  |
| (7) Cash Intensity | -0.107\*\*\* | 0.004 | -0.024 | -0.136\*\*\* | -0.204\*\*\* | -0.152\*\*\* | 1.000 |  |  |  |  |  |
| (8) Tangible Assets | -0.139\*\*\* | 0.155\*\*\* | 0.011 | 0.146\*\*\* | 0.203\*\*\* | 0.380\*\*\* | -0.121\*\*\* | 1.000 |  |  |  |  |
| (9) Labor Intensity | -0.042† | -0.034 | -0.050\* | -0.079\*\* | -0.125\*\*\* | 0.085\*\*\* | 0.025 | 0.347\*\*\* | 1.000 |  |  |  |
| (10) Horizontal Complexity | 0.005 | -0.060\* | 0.153\*\*\* | 0.102\*\*\* | 0.435\*\*\* | 0.028 | -0.017 | 0.014 | -0.085\*\*\* | 1.000 |  |  |
| (11) Spatial Complexity | -0.071\*\* | -0.093\*\*\* | 0.198\*\*\* | 0.146\*\*\* | 0.423\*\*\* | 0.024 | 0.128\*\*\* | 0.021 | -0.085\*\*\* | 0.597\*\*\* | 1.000 |  |
| (12) Interconnected Complexity | -0.078\*\* | 0.040† | 0.081\*\*\* | -0.006 | -0.114\*\*\* | -0.030 | 0.105\*\*\* | 0.008 | -0.062\* | -0.021 | 0.061\* | 1.000 |
| Mean | 0.758 | 0.514 | 0.382 | 0.074 | 6.661 | 0.267 | 0.112 | 0.229 | 5.487 | 15.932 | 0.213 | 0.053 |
| Standard Deviation | 0.164 | 0.499 | 0.486 | 0.190 | 2.227 | 0.278 | 0.127 | 0.230 | 7.088 | 34.330 | 0.231 | 0.059 |

Notes: †*p* < 0.1, \**p* < 0.05, \*\**p* < 0.01, and \*\*\**p* < 0.001 (two-tailed tests).

**Table 3. DID Test Results**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Variables** | **Model 1**  **Baseline DID Model** | **Model 2**  **Use Clustering Standard Errors** | **Model 3**  **Perform**  **Bootstrap Analysis** | **Model 4**  **Measure OE as**  **Sales / Inventory** | **Model 5**  **Measure OE as**  **Sales / PPE** | **Model 6**  **Tobit Model**  **Estimation** | **Model 7**  **Random Effect Estimation** | **Model 8**  **Alternative Treatment Firms Identification** |
| Treatment × Post (H1) | 0.022\*  (2.407) | 0.025\*  (2.033) | 0.022\*  (2.076) | 9.522\*\*\*  (3.593) | 23.965\*  (2.473) | 0.021\*  (2.380) | 0.020\*  (2.243) | 0.013\*  (2.302) |
| Firm Profitability | 0.094\*\*\*  (4.477) | 0.079  (1.447) | 0.094  (1.274) | -8.835  (-1.628) | -21.416  (-1.051) | 0.091\*\*\*  (4.663) | 0.092\*\*\*  (4.675) | 0.004\*  (2.478) |
| Firm Size | -0.022\*\*  (-2.947) | -0.016†  (-1.733) | -0.022\*  (-2.194) | -1.842  (-0.776) | 14.990†  (1.881) | -0.014\*\*\*  (-3.519) | -0.014\*\*\*  (-3.519) | -0.012\*\*\*  (-3.382) |
| Firm Leverage | -0.040\*  (-2.157) | -0.038  (-0.868) | -0.041  (-1.272) | -6.574  (-1.142) | -2.957  (-0.158) | -0.027  (-1.620) | -0.027  (-1.645) | -0.049\*\*\*  (-4.992) |
| Cash Intensity | 0.067\*  (2.132) | 0.085†  (1.912) | 0.067†  (1.689) | -8.594  (-0.941) | 8.613  (0.285) | 0.044  (1.545) | 0.047†  (1.654) | 0.095\*\*\*  (5.301) |
| Tangible Assets | -0.151\*\*\*  (-3.673) | -0.142\*  (-2.256) | -0.151\*\*  (-2.607) | -16.870  (-1.429) | -3.602  (-0.094) | -0.105\*\*\*  (-3.543) | -0.105\*\*\*  (-3.578) | -0.000  (-0.562) |
| Labor Intensity | -0.000  (-0.460) | -0.000  (-0.397) | -0.000  (-0.196) | -1.276\*\*\*  (-4.190) | 0.106  (0.187) | -0.000  (-0.135) | -0.000  (-0.071) | 0.000  (0.597) |
| Horizontal  Complexity | -0.000  (-0.401) | -0.000  (-0.337) | -0.000  (-0.315) | 0.054  (1.150) | 0.235  (1.317) | 0.000  (0.423) | 0.000  (0.218) | -0.006  (-0.495) |
| Spatial  Complexity | -0.007  (-0.035) | -0.018  (-0.766) | -0.007  (-0.273) | -7.252  (-1.318) | -42.090\*  (-2.030) | -0.021  (-0.841) | -0.021  (-1.116) | -0.002  (-1.412) |
| Interconnected  Complexity | -0.035  (-1.325) | -0.095\*  (-2.667) | -0.062  (-1.347) | -13.838  (-1.068) | 60.664  (1.305) | -0.084†  (-1.651) | -0.084†  (-1.853) | -0.027  (-0.845) |
| Constant | 0.938\*\*\*  (17.732) | 0.894\*\*\*  (15.082) | 0.935\*\*\*  (13.336) | 66.123\*\*\*  (3.618) | 88.537  (1.527) | 0.080\*\*\*  (52.099) | 0.870\*\*\*  (31.701) | 0.815\*\*\*  (31.963) |
| Firm Fixed Effects | Yes | Yes | Yes | No | Yes | No | No | Yes |
| Year Fixed Effects | Yes | Yes | Yes | No | Yes | Yes | No | Yes |
| Observations | 1599 | 1599 | 1599 | 1359 | 1610 | 1599 | 1599 | 5010 |
| *F*-value | 5.17\*\*\* | 17.23\*\*\* | N/A | 7.24\*\*\* | 5.98\*\*\* | N/A | N/A | 8.30\*\*\* |
| Wald *X*2 | N/A | N/A | 56.65\*\*\* | N/A | N/A | 100.59\*\*\* | 88.15\*\*\* | N/A |
| *R*2 | 0.072 | 0.073 | 0.072 | 0.061 | 0.054 | N/A | 0.061 | 0.038 |

Notes: †*p* < 0.1, \**p* < 0.05, \*\**p* < 0.01, and \*\*\**p* < 0.001 (two-tailed tests). Unstandardized coefficients are reported. *t*-statistics are in parentheses.

**Table 4. Moderating Effects of Supply Chain Complexity**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Variables** | **Model 1**  **Include Horizontal Complexity** | **Model 2**  **Include**  **Spatial**  **Complexity** | **Model 3**  **Include Interconnected Complexity** | **Model 4**  **Include All**  **Three Complexities** | **Model 5**  **Focus on**  **Upstream Complexity** | **Model 6**  **Focus on**  **Downstream Complexity** |
| Treatment × Post × Horizontal Complexity (H2) | 0.001\*\* (2.644) |  |  | 0.001\*\*\* (3.328) | 0.001\* (1.977) | 0.002\*\*\* (3.784) |
| Treatment × Post × Spatial Complexity (H3) |  | -0.085\* (-1.978) |  | -0.087\* (-2.026) | -0.015 (-0.417) | -0.101\*\* (-2.787) |
| Treatment × Post × Interconnected Complexity (H4) |  |  | 0.018 (0.133) | 0.014 (0.104) | 0.044 (0.321) | 0.023 (0.112) |
| Treatment × Post | 0.019\* (2.112) | 0.022\* (2.424) | 0.022\* (2.407) | 0.022\* (2.351) | 0.021\* (2.224) | 0.023\* (2.364) |
| Firm Profitability | 0.091\*\*\* (4.337) | 0.090\*\*\* (4.296) | 0.094\*\*\* (4.472) | 0.090\*\*\* (4.272) | 0.092\*\*\* (4.388) | 0.090\*\*\* (4.315) |
| Firm Size | -0.020\*\* (-2.707) | -0.020\*\* (-2.640) | -0.022\*\* (-2.948) | -0.020\*\* (-2.709) | -0.021\*\* (-2.842) | -0.021\*\* (-2.800) |
| Firm Leverage | -0.043\* (-2.245) | -0.045\* (-2.330) | -0.041\* (-2.153) | -0.045\* (-2.339) | -0.043\* (-2.228) | -0.047\* (-2.451) |
| Cash Intensity | 0.072\* (2.302) | 0.074\* (2.374) | 0.067\* (2.134) | 0.074\* (2.352) | 0.071\* (2.274) | 0.070\* (2.355) |
| Tangible Assets | -0.153\*\*\* (-3.731) | -0.160\*\*\* (-3.881) | -0.151\*\*\* (-3.671) | -0.157\*\*\* (-3.819) | -0.154\*\*\* (-3.767) | -0.154\*\*\* (-3.752) |
| Labor Intensity | -0.000 (-0.427) | -0.000 (-0.414) | -0.000 (-0.418) | -0.000 (-0.418) | -0.000 (-0.447) | -0.000 (-0.425) |
| Horizontal Complexity | 0.000 (0.545) | 0.000 (0.691) | 0.000 (0.397) | 0.000 (0.689) | -0.000 (-0.743) | 0.001 (1.595) |
| Spatial Complexity | -0.015 (-0.723) | -0.007 (-0.299) | -0.007 (-0.341) | -0.017 (-0.822) | 0.003 (0.177) | -0.024 (-1.439) |
| Interconnected Complexity | -0.060 (-1.272) | -0.063 (-1.345) | -0.061 (-1.303) | -0.067 (-1.426) | -0.062 (-1.330) | -0.077† (-1.650) |
| Constant | 0.925\*\*\* (17.533) | 0.928\*\*\* (17.606) | 0.935\*\*\* (17.716) | 0.926\*\*\* (17.557) | 0.931\*\*\* (17.659) | 0.931\*\*\* (17.643) |
| Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1599 | 1599 | 1599 | 1599 | 1599 | 1599 |
| *F*-value | 5.28\*\*\* | 5.08\*\*\* | 4.92\*\*\* | 5.01\*\*\* | 4.96\*\*\* | 5.60\*\*\* |
| *R*2 | 0.077 | 0.073 | 0.072 | 0.079 | 0.076 | 0.083 |

Notes: †*p* < 0.1, \**p* < 0.05, \*\**p* < 0.01, and \*\*\**p* < 0.001 (two-tailed tests). Unstandardized coefficients are reported. *t*-statistics are in parentheses.

**Table 5. Test Results for Different Channels**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Variables** | **Model 1**  **Impact on**  **Operating**  **Cost** | **Model 2**  **Impact on**  **Production Cost** | **Model 3**  **Impact on**  **Sales**  **Cost** | **Model 4**  **Impact on Inventory**  **Cost** | **Model 5**  **Impact on**  **Labor**  **Cost** | **Model 6**  **Impact on**  **Firm Risk (Monthly)** | **Model 7**  **Impact on**  **Firm Risk**  **(Daily)** | **Model 8**  **Impact on**  **Relationship Stability** |
| Treatment × Post | -0.040\*\*\*  (-4.724) | -0.037\*  (-2.339) | -0.084\*\*\*  (-3.952) | -0.211\*  (-2.466) | -0.005  (-0.174) | -0.024  (-1.205) | -0.011  (-0.642) | 0.056\*  (1.977) |
| Firm Profitability | -0.465\*\*\*  (-26.079) | -0.389\*\*\*  (-11.619) | -0.443\*\*\*  (-9.897) | -0.244  (-1.358) | -0.414\*\*\*  (-5.826) | 0.027  (0.606) | -0.015  (-0.399) | -0.086  (-1.330) |
| Firm Size | 0.977\*\*\*  (88.182) | 1.002\*\*\*  (76.907) | 0.783\*\*\*  (44.906) | 0.957\*\*\*  (13.713) | 0.295\*\*\*  (11.719) | -0.070\*\*\*  (-4.406) | -0.050\*\*\*  (-3.648) | 0.082\*\*\*  (3.618) |
| Firm Leverage | -0.055\*\*\*  (-3.368) | -0.045  (-1.452) | 0.018  (0.440) | -0.245  (-1.485) | -0.168\*  (-2.554) | 0.064  (1.543) | 0.061†  (1.717) | 0.010  (0.173) |
| Cash Intensity | -0.049†  (-1.849) | -0.097†  (-1.957) | -0.178\*\*  (-2.669) | 0.769\*\*  (-2.868) | 0.460\*\*\*  (4.310) | -0.212\*\*  (-3.156) | -0.117\*  (-2.031) | 0.144  (1.486) |
| Tangible Assets | 0.085\*\*  (2.599) | 0.080  (1.312) | 0.049  (0.602) | -0.655\*  (-1.995) | -0.147  (-1.110) | -0.273\*\*  (-3.285) | -0.082  (-1.143) | 0.186  (1.555) |
| Labor Intensity | 0.010\*\*\*  (22.506) | 0.003\*\*\*  (3.877) | 0.014\*\*\*  (12.194) | -0.004  (-0.944) | 0.005\*\*  (2.691) | -0.001  (-1.267) | -0.000  (-0.436) | -0.002  (-0.918) |
| Horizontal Complexity | -0.000  (-0.955) | 0.000  (0.519) | -0.000  (-1.074) | -0.004\*  (-2.532) | -0.000  (-0.680) | -0.000  (-0.349) | -0.000  (-0.494) | 0.000  (0.282) |
| Spatial Complexity | -0.008  (-0.426) | -0.008  (-0.221) | 0.010  (0.228) | 0.472\*\*  (2.589) | -0.112  (-1.550) | 0.044  (0.977) | 0.024  (0.613) | -0.262\*\*\*  (-3.995) |
| Interconnected Complexity | 0.053  (1.299) | -0.072  (-0.939) | 0.026  (0.256) | 0.544  (1.333) | -0.863\*\*\*  (-5.378) | 0.103  (1.021) | -0.082  (-0.945) | 0.170  (1.172) |
| Constant | 0.005  (0.095) | -0.537\*\*\*  (-5.678) | -0.319\*  (-2.513) | -3.842\*\*\*  (-7.542) | 4.423\*\*\*  (25.134) | 0.843\*\*\*  (7.627) | 0.685\*\*\*  (7.209) | 0.418\*\*\*  (6.876) |
| Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1621 | 1621 | 1621 | 1605 | 1310 | 1621 | 1621 | 1621 |
| *F*-value | 512.03\*\*\* | 493.43\*\*\* | 197.79\*\*\* | 21.92\*\*\* | 13.75\*\*\* | 19.79\*\*\* | 37.13\*\*\* | 18.30\*\*\* |
| *R*2 | 0.917 | 0.899 | 0.781 | 0.286 | 0.168 | 0.226 | 0.353 | 0.212 |

Notes: †*p* < 0.1, \**p* < 0.05, \*\**p* < 0.01, and \*\*\**p* < 0.001 (two-tailed tests). Unstandardized coefficients are reported. *t*-statistics are in parentheses.

**Table 6. Impact of Smart Contract Laws on Firms’ Smart Contract Activities**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Variables** | **Model 1**  **Impact of Smart Contract Laws on Smart Contract Adoption (headquarters location sample)** | **Model 2**  **Impact of Smart Contract Laws on Smart Contract Adoption (employee location sample)** | **Model 3**  **Impact of Smart Contract Laws on Smart Contract Talent (headquarters location sample)** | **Model 4**  **Impact of Smart Contract Laws on Smart Contract Talent (employee location sample)** |
| Treatment × Post | 1.003\* (1.981) | 0.602\* (2.011) | 0.604\*\*\* (4.752) | 0.277\* (2.449) |
| Firm Profitability | -1.728 (-1.501) | -0.349\*\* (-2.648) | -0.377 (-1.439) | 0.143 (1.166) |
| Firm Size | 0.568\*\* (3.001) | 0.535\*\*\* (13.306) | 0.333\*\*\* (3.293) | 0.365\*\*\* (4.651) |
| Firm Leverage | -1.459 (-1.277) | -1.456\*\*\* (-4.680) | 0.096 (0.389) | -0.147 (-0.771) |
| Cash Intensity | -6.232\* (-2.111) | -1.838\*\* (-2.650) | 1.882\*\*\* (4.356) | 0.206 (0.530) |
| Tangible Assets | -0.186 (-0.156) | 0.003 (1.271) | -0.428 (-0.796) | -0.034 (-0.073) |
| Labor Intensity | 0.011 (0.144) | 0.033\*\* (2.013) | 0.003 (0.467) | 0.010 (1.316) |
| Horizontal Complexity | 0.004 (1.096) | 0.009\*\*\* (4.680) | 0.003 (1.231) | 0.013\*\*\* (4.506) |
| Spatial Complexity | 1.349† (1.737) | -0.085 (-0.332) | -0.608\* (-2.143) | -0.285 (-1.139) |
| Interconnected Complexity | -1.354 (-0.371) | -2.863\* (-2.086) | 0.081 (0.131) | 0.452 (0.657) |
| Constant | -7.065\*\*\* (-4.565) | -5.982\*\*\* (-16.671) | -2.872\*\*\* (-4.119) | -8.204\*\*\* (-14.605) |
| Firm Fixed Effects | N/A | N/A | Yes | Yes |
| Year Fixed Effects | N/A | N/A | Yes | Yes |
| Observations | 1951 | 6131 | 1951 | 6131 |
| *F*-value | N/A | N/A | 9.77\*\*\* | 21.62\*\*\* |
| Wald *X*2 | 37.00\*\*\* | 361.42\*\*\* | N/A | N/A |
| *R*2 | N/A | N/A | 0.104 | 0.079 |

Notes: †*p* < 0.1, \**p* < 0.05, \*\**p* < 0.01, and \*\*\**p* < 0.001 (two-tailed tests). Unstandardized coefficients are reported. t-statistics are in parentheses.

**Table 7. Impact of Firms’ Smart Contract Activities on Operational Efficiency**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Variables** | **Model 1**  **Impact of Smart Contract Adoption on Operational Efficiency**  **(headquarters location sample)** | **Model 2**  **Impact of Smart Contract Adoption on Operational Efficiency**  **(employee location sample)** | **Model 3**  **Impact of Smart Contract Talent on Operational Efficiency**  **(headquarters location sample)** | **Model 4**  **Impact of Smart Contract Talent on Operational Efficiency**  **(employee location sample)** |
| Smart Contract Adoption × Post Adoption | 0.040\* (2.239) | 0.031\* (2.124) |  |  |
| Smart Contract Talent |  |  | 0.004\*\* (2.809) | 0.001\* (2.423) |
| Firm Profitability | 1.913\*\*\* (13.042) | 1.270\*\*\* (11.027) | 0.081\*\*\* (4.733) | 0.145\*\* (13.796) |
| Firm Size | 0.046\*\* (2.964) | 0.030\* (2.188) | -0.016\* (-2.345) | 0.003 (0.898) |
| Firm Leverage | -0.104† (-1.835) | --0.139† (-1.696) | -0.042\*\* (-2.596) | 0.005 (0.572) |
| Cash Intensity | 0.181 (1.649) | -0.139\* (-1.896) | 0.052† (1.823) | 0.052\*\*\* (2.969) |
| Tangible Assets | -0.401\*\* (-3.156) | -0.323\*\*\* (-4.884) | -0.160\*\*\* (-4.329) | -0.131\*\*\* (-6.139) |
| Labor Intensity | 0.034\*\* (2.983) | 0.007\* (2.264) | -0.000 (-0.580) | 0.001\*\*\* (3.005) |
| Horizontal Complexity | 0.000 (0.435) | -0.001\* (-2.093) | -0.000 (-0.847) | -0.000 (-1.537) |
| Spatial Complexity | 0.069† (1.799) | -0.013 (-0.453) | 0.000 (0.004) | -0.017 (-1.563) |
| Interconnected Complexity | 0.631\*\* (2.879) | 0.090 (0.997) | -0.057 (-1.413) | -0.034 (-1.154) |
| Constant | 0.179 (1.039) | 0.805\*\*\* (7.946) | 0.919\*\*\* (19.317) | 0.728\*\*\* (27.065) |
| Firm Fixed Effects | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 112 | 408 | 1927 | 5803 |
| *F*-value | 28.40\*\*\* | 12.16\*\*\* | 5.93\*\*\* | 21.27\*\*\* |
| *R*2 | 0.071 | 0.074 | 0.066 | 0.079 |

Notes: †*p* < 0.1, \**p* < 0.05, \*\**p* < 0.01, and \*\*\**p* < 0.001 (two-tailed tests). Unstandardized coefficients are reported. *t*-statistics are in parentheses.

**Table 8. Time and Industry Effects**

|  |  |  |
| --- | --- | --- |
| **Variables** | **Model 1**  **Impact Over Time** | **Model 2**  **Impact Across Industries** |
| Treatment × Post (year 1) | 0.012 (1.041) |  |
| Treatment × Post (years 2 to 3) | 0.021\* (1.993) |  |
| Treatment × Post (years 4 to 5) | 0.030\* (2.178) |  |
| Treatment × Post × Wholesale and Retailing |  | 0.052† (1.810) |
| Treatment × Post × Manufacturing and Transportation |  | 0.000 (0.015) |
| Treatment × Post × Services |  | 0.019 (0.684) |
| Control Variables | Yes | Yes |
| Firm Fixed Effects | Yes | Yes |
| Year Fixed Effects | Yes | Yes |
| Observations | 1599 | 1599 |
| *F*-value | 4.71\*\*\* | 4.62\*\*\* |
| *R*2 | 0.072 | 0.071 |

Notes: †*p* < 0.1, \**p* < 0.05, \*\**p* < 0.01, and \*\*\**p* < 0.001 (two-tailed tests). Unstandardized coefficients are reported. *t*-statistics are in parentheses.

**Online Appendix 1.** **Smart Contract Laws (2017 to 2019)**

As shown in Table S1, six smart contract bills were enacted between 2017 and 2019 across five states: Arizona, Tennessee, South Dakota, Arkansas, and North Dakota. The table outlines each bill’s number, its introduction and enactment dates, and a brief summary.

**Table S1. Smart Contract Laws (2017 to 2019)**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **State** | **Bill Number** | **Introduced** | **Enacted** | **Bill Summary** |
| Arizona | HB 2417 | 07-Feb-2017 | 29-Mar-2017 | Recognizes smart contracts in commerce. |
| Tennessee | HB 1507  SB 1662 | 10-Jan-2018 | 22-Mar-2018 | Recognizes the legal authority to use smart contracts in conducting electronic transactions. |
| South Dakota | HB 1196 | 30-Jan-2019 | 07-Mar-2019 | Revises definitions of electronic transmission and contracting to include blockchain. |
| Arkansas | HB 1944 | 27-Mar-2019 | 16-Apr-2019 | Provides that a smart contract shall be a commercial contract. |
| North Dakota | HB 1045 | 03-Jan-2019 | 24-Apr-2019 | Legitimizes smart contracts and electronic signatures in commerce |

**Online Appendix 2.** **Impact of Lobbying Activities on** **Smart Contract Laws**

We measure the lobbying activities of our treatment and control firms in each year using their annual lobbying expenses, which serve as an indicator of their attempts to influence legislation. We obtain data on the lobbying expenses of all sample firms from 2012 to 2022 through LobbyView (Kim, 2018). In this analysis, we use a dummy variable as the dependent variable, indicating whether a state has enacted smart contract legislation. The independent variable is the sample firms’ lobbying expenses during the same period. We also include all control variables from our DID model. As shown in Table S2, firms’ lobbying activities are not significantly related to the enactment of smart contract laws in their states (*p* > 0.1). This suggests that local firms’ lobbying efforts do not significantly influence the passage of smart contract laws, thereby supporting our assumption that the legislative shocks can be treated as exogenous in our research context.

**Table S2. Impact of Lobbying Activities on Smart Contract Laws**

|  |  |
| --- | --- |
| **Variables** | **Model 1** |
| Lobbying Expense | 0.000 (0.402) |
| Firm Profitability | -0.066 (-0.980) |
| Firm Size | 0.001 (0.190) |
| Firm Leverage | -0.182\*\*\* (-3.739) |
| Cash Intensity | 0.068 (0.720) |
| Tangible Assets | 0.614\*\*\* (10.195) |
| Labor Intensity | -0.008\*\*\* (-5.334) |
| Horizontal Complexity | -0.000 (-0.134) |
| Spatial Complexity | -0.271\*\*\* (-4.683) |
| Interconnected Complexity | 0.271 (1.453) |
| Constant | 0.450\*\*\* (7.729) |
| Year Fixed Effects | Yes |
| Observations | 1951 |
| *F*-value | 7.60\*\*\* |
| *R*2 | 0.073 |

Notes: †*p* < 0.1, \**p* < 0.05, \*\**p* < 0.01, and \*\*\**p* < 0.001 (two-tailed tests). Unstandardized coefficients are reported. *t*-statistics are in parentheses.

**Reference**

Kim, I. S. (2018). LobbyView: Firm-level Lobbying & Congressional Bills Database. *MIT Working Paper*, Available from: http://web.mit.edu/insong/www/pdf/lobbyview.pdf.

**Online Appendix 3. Reverse Causality Tests**

We check the potential reverse causality that the enactment of smart contract laws is influenced by firms’ operational efficiency. If this were the case, it would have introduced endogeneity concerns and weaken our identification strategy. To address this issue, we follow prior research (e.g., Lin et al., 2021) and employ a Weibull hazard model to examine whether firm-level operational efficiency affects the timing of smart contract law enactment. In our Weibull hazard model, the sample includes all firms with headquarters data from 2012 to 2022. The dependent variable is a dummy variable coded as 1 if a firm is headquartered in a state that enacted smart contract legislation in a given year and 0 otherwise. The independent variable represents firms’ operational efficiency, which is measured in three alternative ways (i.e., the SFA approach, Sales / Inventory, and Sales / PPE). As documented in Table S3, the coefficients of the three operational efficiency measures are all insignificant (*p* > 0.1) across Models 1 to 3. These results suggest that operational efficiency does not influence the timing of smart contract law enactment, reducing the reverse causality concern.

**Table S3. Reverse Causality Test**

|  |  |  |  |
| --- | --- | --- | --- |
| **Variables** | **Model 1** | **Model 2** | **Model 3** |
| Operational Efficiency  (Measured based on the SFA approach) | -0.207  (-1.001) |  |  |
| Operational Efficiency  (Measured as Sales / Inventory) |  | 0.000  (0.780) |  |
| Operational Efficiency  (Measured as Sales / PPE) |  |  | 0.000  (0.145) |
| Constant | 4.068\*\*\*  (24.852) | 3.818\*\*\*  (64.904) | 3.945\*\*\*  (69.850) |
| Log pseudolikelihood | -594.437 | -512.105 | -614.766 |
| Wald *X*2 | 1.00 | 0.61 | 0.02 |
| Observations | 31793 | 26227 | 33236 |

Notes: †*p* < 0.1, \**p* < 0.05, \*\**p* < 0.01, and \*\*\**p* < 0.001 (two-tailed tests). Unstandardized coefficients are reported. *t*-statistics are in parentheses.

**Reference**

Lin, C., Liu, S., & Manso, G. (2021). Shareholder litigation and corporate innovation. *Management Science*, *67*(6), 3346-3367.

**Online Appendix 4: Spillover Effects of Smart Contract Laws**

We examine the potential violation of SUTVA arising from the spillover effects from treatment firms to control firms. To do so, we create a dummy variable, *Geographical Proximity*, which indicates whether a firm in a control state is geographically adjacent to any of the five states that enacted smart contract laws. We then estimate a three-way interaction effect between Geographical Proximity, Treatment, and Post to examine whether firms in these adjacent control states experience any indirect benefits. The test results, reported in Table S4, show that the coefficient of the interaction term (i.e., *Treatment×Post×Geographical Proximity*) is not statistically significant (*p* > 0.1). This suggests that firms headquartered in control states with geographical adjacency to states that enacted smart contract laws do not experience spillover effects from the enactment of these laws, supporting the validity of the SUTVA assumption.

**Table S4. Spillover Effects of Smart Contract Laws**

|  |  |
| --- | --- |
| **Variables** | **Model 1** |
| Treatment × Post × Geographical Proximity | -0.026 (-1.016) |
| Treatment × Post | 0.027\*\* (2.597) |
| Firm Profitability | 0.093\*\*\* (4.448) |
| Firm Size | -0.022\*\* (-2.984) |
| Firm Leverage | -0.042\* (-2.192) |
| Cash Intensity | 0.067\* (2.154) |
| Tangible Assets | -0.150\*\*\* (-3.636) |
| Labor Intensity | -0.000 (-0.440) |
| Horizontal Complexity | -0.000 (-0.561) |
| Spatial Complexity | -0.006 (-0.262) |
| Interconnected Complexity | -0.061 (-1.310) |
| Constant | 0.937\*\*\* (17.757) |
| Firm Fixed Effects | Yes |
| Year Fixed Effects | Yes |
| Observations | 1599 |
| *F*-value | 4.97\*\*\* |
| *R*2 | 0.072 |

Notes: †*p* < 0.1, \**p* < 0.05, \*\**p* < 0.01, and \*\*\**p* < 0.001 (two-tailed tests). Unstandardized coefficients are reported. *t*-statistics are in parentheses.

**Reference**

Keele, L. J., & Titiunik, R. (2015). Geographic boundaries as regression discontinuities. *Political Analysis*, 23(1), 127-155.

**Online Appendix 5. Digitalization Level Differences Between Treatment and Control States**

It is possible that the operational efficiency improvement documented in our research may be driven by treatment states’ high digitalization levels rather than by their enactment of smart contract legislation, raising a concern about the causal relationship between smart contract legislation and firms’ operational efficiency. To address this concern, we compare the digitalization levels of states that have enacted smart contract legislation (treatment states) with those that have not (control states). We collect the digitalization level data for both treatment states and control states from the Digital States Survey for the years 2016, 2018, and 2020, covering the period of the smart contract laws investigated in our research (i.e., 2017-2019). The Digital States Survey is a biennial assessment that evaluates the digitalization levels of US state governments and assigns each state a grade based on quantifiable rank (Bui et al., 2023). To facilitate our analysis, we convert these grades into a point system, where the highest rank (A) equals 9 points, and the lowest rank (D) equals 1 point. We then incorporate this data into our analysis to compare the digitalization levels between the treatment and control states. The test results are documented in Table S5. Our findings indicate that there is no significant difference (*p* > 0.1) in the digitalization level between the treatment and control states across the period from 2016 to 2020. Similarly, when examining individual years (2016, 2018, and 2020), we also could not find significant differences in the digitalization level between the two groups. Consequently, the effects observed in our study are less likely to be driven by the treatment states’ high digitalization levels rather than by their enactment of smart contract legislation.

**Table S5. Digitalization Level Differences Between Treatment and Control States**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Variables** | **Treatment** | **Control** | **Difference** | ***t*-statistics** | ***p*-value** |
| Digitalization Level over Years 2016 to 2020 | 6.533 | 6.736 | -0.203 | -0.494 | 0.623 |
| Digitalization Level in Year 2016 | 6.400 | 6.448 | -0.048 | -0.061 | 0.952 |
| Digitalization Level in Year 2018 | 6.400 | 6.690 | -0.290 | -0.400 | 0.692 |
| Digitalization Level in Year 2020 | 6.800 | 7.068 | -0.268 | -0.441 | 0.662 |

**Reference**

Bui, Q., Bui, S., & Lee, G. M. (2023). Effects of Digital Transformation Initiatives on IT Performance: Evidence from US State Governments. *Digit 2023 Proceedings*.

**Online Appendix 6. Pre-shock Differences between Treatment and Matched Control Firms**

We conduct several tests to check the quality of our matching approach. First, we check the differences between treatment and matched control firms in terms of the three variables used for matching. The test results documented in Panel A of Table S6 suggest that treatment and matched control firms have similar average firm size, firm profitability, and operational efficiency over a five-year pre-shock period. Panel B of the same table further shows that in each of the five years before the shock, there is no significant difference in operational efficiency between treatment and matched control firms. As an additional verification, we follow Lam et al. (2022) and perform a parallel trend test. The test results covering five years before to five years after the enactment of smart contract laws are plotted in Figure S1. Given that the enactment year serves as the reference group, it is omitted from Figure S1. Over the five-year pre-treatment period (i.e., years -5 to -1), the points of the estimated coefficients closely align with the horizontal zero line, and their corresponding 90% confidence intervals demonstrate no evidence of a significant pre-trend difference in operational efficiency between treatment and matched control firms. Taken together, these test results indicate the similarity between treatment and matched control firms in the pre-treatment period and demonstrate our matching quality.

**Table S6. Differences between Treatment and Matched Control Firms**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Panel A: Pre-Shock Five-Year Average Values** | | | | | |
| Variable | Treatment | Control | Difference | *t*-statistics | *p*-value |
| Firm Size | 6.285 | 6.234 | 0.051 | 0.171 | 0.864 |
| Firm Profitability | 0.069 | 0.057 | 0.012 | 0.457 | 0.648 |
| Operational Efficiency | 0.761 | 0.773 | -0.012 | -0.703 | 0.483 |
| **Panel B: Pre-Shock Five-Year Values** | | | | | |
| Variable | Treatment | Control | Difference | *t*-statistics | *p*-value |
| Operational Efficiency(*t*-5) | 0.747 | 0.782 | -0.035 | -1.019 | 0.313 |
| Operational Efficiency(*t*-4) | 0.774 | 0.748 | 0.025 | 0.645 | 0.523 |
| Operational Efficiency(*t*-3) | 0.782 | 0.790 | -0.008 | -0.209 | 0.835 |
| Operational Efficiency(*t*-2) | 0.745 | 0.772 | -0.027 | -0.418 | 0.679 |
| Operational Efficiency(*t*-1) | 0.754 | 0.779 | -0.025 | -0.628 | 0.534 |

Note: Year *t* is the year of enacting smart contract legislation.

**A graph with numbers and lines

Description automatically generatedFigure S1. Parallel Trend Test**

Note: the year of enacting smart contract legislation serves as the reference group.

**Online Appendix 7. Sensitivity Tests based on Different Matching Approaches and Alternative Estimation Periods**

We conduct several tests to examine whether our findings are sensitive to different matching approaches and alternative estimation periods. The test results are documented in Table S7. We first check whether our test results are sensitive to different matching approaches. In particular, when performing MDM, we change the caliber value from 0.05 to 0.03 (Model 1). We also perform the matching without replacement rather than with replacement (Model 2). Moreover, instead of performing the matching based on Mahalanobis distance, we also follow Shen et al. (2023) and employ a kernel-matching approach to construct our control firms (Model 3). The test results based on these different matching approaches remain consistent, as shown in Models 1 to 3 of Table S7.

We then employ alternative estimation periods. Specifically, when performing the DID estimation, we include all available observations in the period of 2012-2022 (Model 4), without limiting to those falling in the period of 5 years before to 5 years after the enactment of the smart contract laws (-5, +5). Moreover, as our investigation period, spanning from 2012 to 2022, overlaps with the COVID-19 pandemic, we rerun the DID estimation by excluding all observations during the COVID-19 pandemic (i.e., from years 2020 to 2022) (Model 5). The coefficients of *Treatment × Post* remain positive and significant (*p* < 0.05) based on these alternative estimation periods, as shown in Models 4 and 5 of Table S7.

**Table S7. DID Test Results (Different Matching Approaches and Estimation Periods)**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Variables** | **Model 1**  **Use 0.03**  **Caliber**  **Value** | **Model 2**  **Match**  **Without Replacement** | **Model 3**  **Employ**  **Kernel Matching** | **Model 4**  **Include**  **All Years in Estimation** | **Model 5**  **Exclude 2020-2022 from Estimation** |
| Treatment × Post (H1) | 0.027\*\*  (2.893) | 0.021\*  (2.267) | 0.031\*\*\*  (3.375) | 0.018\*  (2.204) | 0.023\*  (2.264) |
| Firm Profitability | 0.086\*\*\*  (4.109) | 0.093\*\*\*  (4.415) | 0.228\*\*\*  (8.665) | 0.077\*\*\*  (4.501) | 0.078\*\*\*  (4.161) |
| Firm Size | -0.022\*\*  (-2.935) | -0.021\*\*  (-2.812) | -0.012  (-1.538) | -0.014\*  (-2.135) | -0.020\*  (-2.351) |
| Firm Leverage | -0.047\*  (-2.438) | -0.041\*  (-2.104) | -0.042\*  (-2.130) | -0.040\*  (-2.468) | 0.040\*  (2.152) |
| Cash Intensity | 0.058†  (1.837) | 0.068\*  (2.155) | 0.015  (0.463) | 0.057\*  (2.019) | 0.074\*  (2.569) |
| Tangible Assets | -0.162\*\*\*  (-3.906) | -0.148\*\*\*  (-3.556) | -0.194\*\*\*  (-4.635) | -0.169\*\*\*  (-4.545) | -0.212\*\*\*  (-5.379) |
| Labor Intensity | -0.000  (-0.398) | -0.000  (-0.435) | -0.000  (-0.096) | -0.000  (-0.577) | -0.000  (-0.413) |
| Horizontal  Complexity | -0.000  (-0.337) | -0.000  (-0.392) | -0.000  (-0.144) | -0.000  (-0.690) | 0.000  (1.622) |
| Spatial  Complexity | -0.011  (-0.504) | -0.008  (-0.382) | 0.003  (0.133) | -0.002  (-0.100) | -0.041\*  (-2.027) |
| Interconnected  Complexity | -0.061  (-1.303) | -0.061  (-1.276) | -0.057  (-1.217) | -0.059  (-1.468) | -0.066  (-1.433) |
| Constant | 0.938\*\*\*  (17.750) | 0.932\*\*\*  (17.479) | 0.868\*\*\*  (16.360) | 0.894\*\*\*  (19.177) | 0.923\*\*\*  (15.810) |
| Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 1556 | 1574 | 1480 | 1927 | 1181 |
| *F*-value | 5.25\*\*\* | 5.01\*\*\* | 8.60\*\*\* | 5.76\*\*\* | 6.48\*\*\* |
| *R*2 | 0.075 | 0.071 | 0.122 | 0.065 | 0.107 |

Notes: †*p* < 0.1, \**p* < 0.05, \*\**p* < 0.01, and \*\*\**p* < 0.001 (two-tailed tests). Unstandardized coefficients are reported. *t*-statistics are in parentheses.

**Online Appendix 8. Placebo Test**

Following previous studies (e.g., Lam et al., 2022), we perform a placebo test to examine whether the operational efficiency improvement documented in our study is indeed caused by the enactment of smart contract laws rather than other unobservable factors (e.g., the introduction of other non-smart contract regulations). Specifically, we randomly assign the interaction term, *Treatment × Post*, to all sample firms. This random assignment generates a “false” effect of smart contract laws on operational efficiency. If the interaction term becomes insignificant after this random assignment process, the placebo test suggests that the increase in operational efficiency is indeed caused by the real enactment of smart contract laws. However, if the interaction term is still significant after the random assignment, our results may be biased due to potentially unobservable factors. After repeating the DID estimation 1,000 times based on the random assignment of the interaction term, we plot the estimated coefficients and associated *t*-values of the falsified *Treatment × Post* term in Figure S2. As shown in Figure S2a, the solid line indicating the average coefficient of the falsified *Treatment × Post* term is centered around zero. Similarly, Figure S2b shows that the *t*-values of the estimated coefficients are also centered around zero and mostly lower than 2, indicating that most of the falsified *Treatment × Post* values are not significant. The placebo test results confirm that our findings are more likely due to the enactment of smart contract laws than other unobservable factors.

**Figure S2. Placebo Test Results**

|  |  |
| --- | --- |
| A graph of a normal distribution  Description automatically generated | A diagram of a normal distribution  Description automatically generated |
| **Figure S2a. Density Plot of Estimated Coefficients** | **Figure S2b. Density Plot of *t*-Statistics** |

**Reference**

Lam, H. K., Ding, L., & Dong, Z. (2022). The impact of foreign competition on domestic firms' product quality: Evidence from a quasi‐natural experiment in the United States. *Journal of Operations Management*, *68*(8), 881-902.

1. We sincerely thank the editors and reviewers for their critical and important comments over the past few rounds of reviews. [↑](#footnote-ref-1)
2. In the reference papers, upstream horizontal supply chain complexity is measured as the number of direct suppliers in the supply base. In our context, we modify the measurement and use the total number of direct supply chain partners (including suppliers and customers) to cover both upstream and downstream supply chains which are both related to smart contract adoption. [↑](#footnote-ref-2)
3. Our test results remain consistent if we use 10% instead of 5% as the cutoff point. [↑](#footnote-ref-3)
4. To ensure the robustness of our findings, we conduct the searches and analyses for two sets of sample firms: the first set is identified based on headquarters locations, with a total of 242 sample firms, including 124 treatment firms and 118 matched control firms (see section 3.3); and the second set is identified based on employee locations, with a total of 824 sample firms, including 433 treatment firms and 391 matched control firms (see section 4.1). [↑](#footnote-ref-4)
5. We conduct a manual, intensive search via different online databases such as Factiva, SEC Filings, and Google News to identify US-listed firms with smart contract adoption. We are able to identify 107 US-listed firms that had adopted smart contracts from 2012 to 2022 (our investigation period). As the total number of US-listed firms in this period was 13827 based on the information obtained from Compustat, the average smart contract adoption rate of US-listed firms was 0.77% (107/13827) from 2012 to 2022. [↑](#footnote-ref-5)