Impact of Credit Default Swaps on Firms' Operational Efficiency

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Liangfei Qiu
Warrington College of Business
University of Florida, Gainesville, Florida 32611
E-mail: liangfei.qiu@warrington.ufl.edu
Phone: 352-294-7183

Ruiqi Liu*
*Corresponding author
School of Accounting & Finance, PolyU Business School
The Hong Kong Polytechnic University, Hung Hom, Hong Kong 999077
Email: ruiqi.liu@connect.polyu.hk
Phone: 852-27667716

Yong Jin
School of Accounting & Finance, PolyU Business School
The Hong Kong Polytechnic University, Hung Hom, Hong Kong 999077
Email: jimmy.jin@polyu.edu.hk
Phone: 852-27665612

Chao Ding
HKU Business School
The University of Hong Kong, Pokfulam, Hong Kong 999077
E-mail: chao.ding@hku.hk
Phone: 852-39171684

Yangyang Fan
School of Accounting & Finance, PolyU Business School
The Hong Kong Polytechnic University, Hung Hom, Hong Kong 999077
Email: yangyang.fan@polyu.edu.hk
Phone: 852-27667072

Andy C. L. Yeung
Department of Logistics and Maritime Studies, PolyU Business School
The Hong Kong Polytechnic University, Hung Hom, Hong Kong 999077
Email: andy.yeung@polyu.edu.hk
Phone: 852-27664063

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Abstract

As one of the most important financial innovations in the last two decades, credit default swap (CDS) contracts have been initiated and actively traded in the market to hedge against credit risks. However, little is known about how these financial innovations affect an underlying firm's operations. In this empirical study, we find that an underlying firm's operational efficiency is significantly improved with the inception of CDS trading. Our results are robust to multiple causal identification strategies. Further analysis suggests that the inception of CDS tends to enhance the operational efficiency of a firm through the supply chain financing capability and trade credit. We also postulate that CDS leads to enhanced efficiency through institutional monitoring and improvements in management effectiveness. We then obtain suggestive evidence. Our findings have direct implications concerning the ongoing policy debate surrounding CDS. We contribute to operations management research by exploring how innovations in the financial market would, in turn, affect the operational performance of firms.

Keywords: *Financial Innovations; Credit Default Swaps; Operational Efficiency; Supply Chain Finance; Institutional Monitoring*

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"I wish somebody would give me some shred of evidence linking financial innovation with a benefit to the economy."

— Paul Volcker (2009), former Chair of the Federal Reserve

1. Introduction

As one of the most important financial innovations in the last two decades, credit default swap (CDS) contracts have increasingly been initiated and actively traded in the market to hedge against credit risks. The CDS market experienced explosive growth since 2000 and reached $62 trillion in notional value in 2007, and the most recent market size is approximately $15–20 trillion (Chang et al. 2019). A CDS is a fixed-income derivative instrument: Buyers pay a periodic premium (i.e., CDS spread) to sellers in exchange for compensation when credit events of underlying assets occur. Credit events can be failures to pay interest or principal, bankruptcy, or even credit rating downgrades. For example, if an underlying reference firm fails to meet its debt obligations, then, the CDS contract would help the buyer receive a payoff from the seller, which usually equals the difference between the face value and the underlying obligation value. If the underlying asset of the CDS contract is a firm's debt, then, the CDS contract can help lenders hedge the potential credit risk associated with the debt. As one of the most important fixed income derivative securities in the market, CDSs are frequently viewed as "side bets" and initiated by the financial institutions (Subrahmanyam et al. 2014)—the nature of "side bets" does not directly change the fundamentals of the underlying firms and their operations, whereas the CDS trading may affect firms' management including operations managers' decision making and influence the markets' views about the underlying firms. Consequently, although the CDS contracts are mostly traded by the financial institutions, the underlying reference firms' daily operations may also be affected by the presence of these major financial innovations in the financial market.

The debate on the role of CDS has been steadily growing, especially after the credit crisis of 2007–2009. On the one hand, CDS spreads are believed to be accurate in measuring firms' credit quality. On the other hand, CDS contracts were central to the credit crisis of 2007–2009. CDS contracts can fundamentally affect the behaviors of borrowers (the underlying reference firms) and lenders by changing their risk-sharing mechanisms. Prior studies have focused on the financial implications of CDS, such as the impact of CDS trading on banks' incentives to engage in costly monitoring (Bolton and Oehmke 2011), the impact of CDS on credit supply to underlying firms (Saretto and Tookes 2013), and the impact of CDS on corporate bonds (Shim and Zhu 2014). However, the operational implications of CDS have not been well understood. To the best of our knowledge, little is known about the impact of the inception of CDS on operational efficiency as well as the channels through which CDS affects operational efficiency.[1] In this empirical study, we examine how a specific form of external financial innovations (e.g., CDS) contributes to operational efficiency through supply chain finance and institutional monitoring.

To enrich our understanding of the relation between CDS and operational efficiency, we pose our first research question: (1) *What is the influence of financial innovations, such as the inception of CDS, on operational efficiency?* CDSs can serve as efficient monitoring tools, as firms' credit quality can be quantified by CDS spreads.[2] In addition, CDS trading reduces asymmetric information such that supply chain partners can more easily monitor underlying reference firms, thereby increasing their firms' operational efficiency. CDS markets can provide outsiders with valuable information, such as the credit risks of the underlying reference firms (Saretto and Tookes 2013). Specifically, supply chain partners can more effectively monitor credit risk, which effectively increases the willingness of supply chain partners to provide trade credit. Therefore, underlying reference firms can obtain higher trade credit through supply chain finance and improve operational efficiency. Given that CDS trading can effectively reduce information asymmetry, prior studies show that the inception of CDS allows firms to borrow more at longer maturities and at lower interest rates (Augustin et al. 2014). Following this logic, we demonstrate in our study that the inception of CDS can increase the operational efficiency of underlying reference firms.

An empirical challenge in answering the first research question is to establish the *causal* effect of the inception of CDS, considering that CDS trading is endogenously determined. Factors that contribute to a firm's operational efficiency may also affect the likelihood of CDS inception. Without addressing this selection issue, our estimation of the effect of CDS would be biased. In this study, we use several identification strategies to validate the causal effect and provide the first empirically driven, comprehensive understanding of CDS trading's impact on underlying reference firms' operational efficiency. Specifically, we show that financial innovations (i.e., CDS trading) contribute positively to operational efficiency. Our results are robust to different empirical measures of operational efficiency and different empirical strategies, such as the Heckman-type models, propensity score matching (PSM), coarsened exact matching (CEM), and instrumental variable approaches.

Prior studies have not directly addressed the channel through which CDS trading can affect operational efficiency, thereby motivating us to pose the second research question: (2*) How does the inception of CDS affect operational efficiency through supply chain finance?*

Bolton and Oehmke (2011) suggest that CDS trading can theoretically enhance firms' debt capacities; therefore, CDSs may promote corporate operational efficiency through a supply chain financing

[1] Alan et al. (2014) find that operational efficiency can predict financial outcomes (e.g., future stock returns). Our research focuses on the impact of financial innovations on operational efficiency.
[2] Prior studies find that CDS can substitute for the role of credit ratings. For example, Chava et al. (2018) show that CDS trading can decrease the sensitivity between a firm's stock price and credit rating downgrades.

channel. Trade credit, one major short-term loan that exists in supply chain finance, allows customers to delay the payment of an invoice to suppliers. Trade credit has been extensively used in supply chain daily operations—by offering the trade credit, the suppliers can finance the customers at a lower cost (than the financial institutions) and maintain the customer–supplier relationship; in addition, both sides can keep the payment flexibility and thus reduce the excessive need to maintain precautionary balances. Trade credit also mitigates information asymmetry (Smith 1987). However, the trade credit for one underlying firm is not unlimited, which is bounded by its credit rating and the firm's fundamentals. Given that CDS trading can enhance firms' debt capacities, including the trade credit, then firms can improve trade credit and establish more efficient supply chains with financial innovations.

We contribute to the operations management (OM) research by exploring how innovations in the financial market would, in turn, affect the operational performance of firms. Researchers have long been interested in how external forces, such as those in the financial market, would have an impact on the internal operations and capabilities, leading to heterogeneous levels of efficiency and competitive outcome (Craighead et al. 2009; Hitt et al. 2016; Wu et al. 2019). Kumar et al. (2020) also request research incorporating disruptive financial innovation and operations. In this research, we show that the inception of CDS tends to enhance the operational efficiency of a firm through the supply chain financing capability and trade credit. We also postulate that CDS leads to enhanced efficiency through institutional monitoring and improvements in management effectiveness. We then obtain some support. Our research helps scholars understand how competitive advantage can be generated as firms are positioned differently in the financial market and how efficiency and competitiveness can be generated in a very different way. We show that the efficiency and competitive advantage of firms are not only generated internally through better systems and routines within the firm. Instead, we demonstrate them as potentially generated through external resources and advantages, such as a different positioning through financial innovation. Our findings have important practical implications. We also suggest that the firms' management should also pay attention to and react to financial markets and financial innovations even those not directly related to firms' operations. Additionally, the resources and advantages from external could be well integrated with firms' operations. We further establish firms' additional efficiency and competitive advantage. The firms' management may also enhance the newly established competitive advantage in internal governance, deal negotiation (debt dependency), supply chain management, risk management, and firms' overall financial performance.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 provides a detailed description of our dataset and further introduces the key variable in our empirical analysis. Section 4 details the discussion of our baseline empirical results and several additional tests. We conclude this paper in Section 5.

2. Literature Review, Theory, and Research Hypotheses

Our literature review is based on two different strands: (i) CDSs and financial innovations in the finance literature and (ii) operational efficiency in the OM literature. We highlight the contributions of this study by contrasting our results with those in prior literature.

2.1. Credit Default Swaps

The initiation of CDS adds to the credit risk transfer channel for bank lenders and bondholders. Specifically, by obtaining compensation from CDS sellers in a credit event, lenders somewhat transfer the borrowers' credit risk to CDS sellers (Martin and Roycowdhury 2015), which changes the relationship between lenders and borrowers. Morrison (2005) and Parlour and Winton (2013) model that CDS may lead to financial disintermediation as well as reduced incentives of banks to monitor and intervene. In addition, the inception of CDS should enhance lenders' bargaining power in debt renegotiations and therefore relax borrowers' debt contract constraints and increase borrowers' debt capacity (Bolton and Oehmke 2011). Some empirical evidence provides support for this theoretical analysis. For instance, Saretto and Tookes (2013) find that CDS increases lenders' willingness to lend, which increases firms' leverage and debt maturity. Shan et al. (2015) show evidence that CDS trading affects loan contracts by lowering the requirements on collateral and borrowers' minimum net value. Ivanov et al. (2016) show that for loans with interest rates tied to issuers' CDS spreads, banks would set a lower interest rate and more simple covenants. Others have found that these effects can only apply to certain borrowers. For example, Ashcraft and Santos (2009) find a higher borrowing cost for high-risk borrowers but a lower borrowing cost for low-risk borrowers after the inception of CDS trading. Moreover, Kim (2013) shows that after the initiation of CDS trading, corporate bond spreads decrease more for firms with higher strategic default incentives. With the changes to lender–borrower relations and firms' debt capabilities as the CDS trading effects, firms' operation outputs may also be affected. Chang et al. (2019) reveal that CDS can enhance lenders' risk tolerance and facilitate borrowers' risk-taking behavior and can therefore improve borrowing firms' innovation quality. Figure 1 shows the entities that are involved in the CDS contracts and their relations.

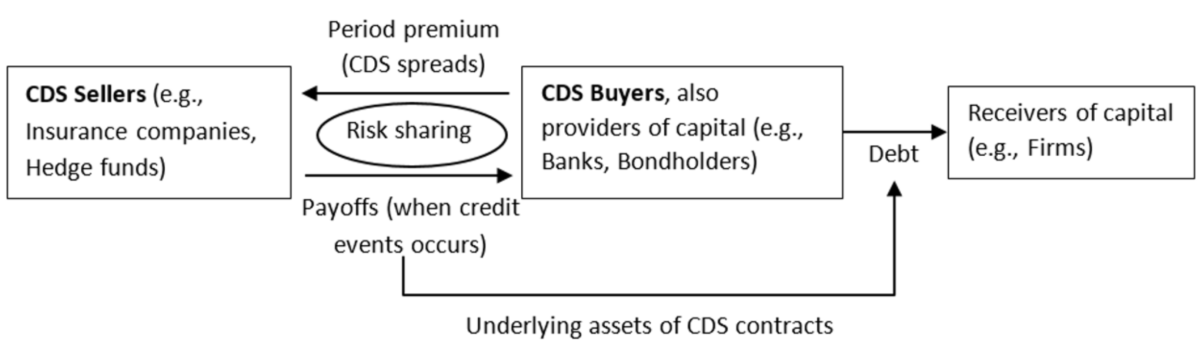

Figure 1. Credit Default Swap (CDS) Contracts

2.2. Operational Efficiency

Prior studies indicate that a firm's resources, routines, and capabilities are three major factors that explain a firm's relative performance concerning operational efficiency (Peng et al. 2008; Lam et al. 2016). Among these factors, resources include tangible and intangible productive assets, routines refer to internal corporate governance within an organization, and capabilities consist of information and knowledge exchange across management and organizations (Kusunoki et al. 1998). Lam et al. (2016) find that firms' social media initiatives positively affect firms' operational efficiency by facilitating information flow and knowledge sharing within and across organizations (i.e., the routines and capacities channels). In turn, CDS trading may affect the resources channel (Bolton and Oehmke 2011) and the capacities channel (Chang et al. 2019); thus, the operational efficiency of underlying firms may be further influenced. More specifically, with the inception of CDS for an underlying firm, the firm's attractiveness, standing, and advantage in the external financial market might, in turn, affect its internal resources, routines, and capabilities. From a resource-based view (RBV) of the firm, the persistent internal and operational advantage might be derived from the positional advantage in the capital market and shaped by external forces (see e.g., Parmigiani et al. 2011) as a firm is differently positioned in the investment community due to CDS trading. Indeed, the literature has documented that a firm's position in the financial market and its relationship with other stakeholders, including financial institutions and supply chain partners, might actually affect its policy, strategy, management practice, and internal control (Johnson and Greening 1999; Parmigiani et al. 2011; Wu et al. 2019), leading to differentiating levels of operational efficiency and competitive advantage. We will provide a more detailed explanation below and develop our hypotheses accordingly.

2.3. Theory and Research Hypotheses

We first explore the CDS' overall impact on firms' operational efficiency: on the one hand, the inception of the CDS enhances the supply chain credibility and the resource-based advantage. Therefore, the presence of CDS may further enhance operational efficiency. On the other hand, the inception of the CDS stimulates improved stakeholder monitoring, governance, and control. On this channel, we conclude that the presence of CDS may also improve operational efficiency. Hence we have the first hypothesis:

> H1: The inception of CDS leads to the higher operational efficiency of the underlying firm in general.

After examining the main hypothesis, we would like to exploit the possible channels and develop the possible theory and corresponding hypotheses.

2.3.1. *Supply Chain Credibility and Resource-based Advantage*

Scholars in OM have long been interested in how heterogeneous resource advantages lead to fundamentally and persistently different organizational routines, supply chain capabilities, and firm efficiency levels (Craighead et al. 2009; Hitt et al. 2016; Wu et al. 2019; Kumar and Qiu 2022), resulting in different resource-generating abilities and competitive positions. The RBV of the firm suggests that the competitive advantage of a firm is not generated directly by possessing resources but by how firms leverage these resources to derive stronger positional advantages and competitive outcomes (Hitt et al. 2016; Song et al. 2011). Superior resources and positional advantages enable firms to be both more productive and effective than their rivals in a competitive marketplace (Song et al. 2011). We argue that the inception of CDS for a reference firm enables the underlying firm to gain a certain positional advantage in the financial market and the supply chain over their rivals in the same industry, leading to higher operational efficiency.

First, the inception of CDS empowers firms with higher visibility and information transparency. Information sharing across supply chains and partner firms could help make better operational decisions and increase efficiency (Kumar et al. 2018b). Before the inception of CDS, operational and financial information about the underlying firm is likely limited to the banks and other financial institutions that make direct transactions with the underlying firm at a specific time. With CDS trading, the operational and financial positions of the underlying firms become a widespread and persistent concern in the investment community. For example, with the initiation of CDS trading, the market as a whole, including the CDS issuers, the traders, the credit rating agencies, and others, would be increasingly interested in the underlying operating performance and financial position of the firm. As a result of CDS trading, the market attentiveness and information transparency of the underlying firm are enhanced. Consequently, organizational visibility, creditability, and firm’s legitimacy in the market due to CDS trading become an important positional advantage, leading to a higher reputation and standing of the underlying firm among supply chain partners and the business community (Burkart and Ellingsen 2004; Ng et al. 1999). This situation enables the underlying firm to improve its supply chain financing capability and resources, particularly through trade credit. From an RBV, such an external positional advantage and supply chain financing capability enable the firm to gain a higher level of operational efficiency (Hitt et al. 2016; Wuttke et al. 2019).

> H2a: The inception of CDS leads to the higher operational efficiency of the underlying firm mediating through supply chain financing resources such as trade credit.

2.3.2. *Stakeholder Monitoring, Governance, and Control*

Stakeholder theory (Freeman 1999) provides another useful framework to explain another possible path that CDS might lead to the higher operational efficiency of the underlying firm. According to the instrumental perspective of stakeholder theory, systematic attention of a firm to stakeholder interests is critical for the operational and economic benefits of the focal firm (Berman et al. 1999). Stakeholders are defined as any group or individual, such as shareholders, creditors, customers, and suppliers, who are likely to affect or to be affected by the operations of an organization (Berman et al. 1999; Barth et al. 2013). As stakeholders might be influenced by the operations and achievements of the firm's objectives, they are naturally interested and concerned about the activities and decisions of the focal firm (Harrison and Wicks 2013).

With the inception of CDS, the operations, activities, and decisions of the underlying firm tend to be an increasing concern of many stakeholders, including CDS issuers, CDS traders, credit rating agencies, and others. Such an increased concern of stakeholders may lead to improved corporate governance and internal control of the underlying firms. For example, with increased attentiveness, monitoring, and pressure from stakeholders (e.g., CDS issuers and holders), any customer complaint or negative corporate incident of the focal firm is likely to draw extra attention from the business community and is thus a heightened concern of the management of the firm. Previous research has shown that institutional investors have a strong interest not only in the financial performance of their investment firms but also in the firms' activities, operations, and strategies (Johnson and Greening 1999; Barth et al. 2013). The interests of stakeholders in the investment community are linked to their increased involvement in the governance and management of the underlying firm (Johnson and Greening 1999).

From the perspective of stakeholder theory, systematic attention to the stakeholders by the focal firm or an instrumental posture of the firm toward stakeholders is an important step for firms to maintain their legitimacy and efficiency, reducing transaction costs and maximizing their own economic benefits (Berman et al. 1999; Johnson and Greening 1999; Jacobs et al. 2016). Consequently, the focal firm is willing to "cooperate" with other stakeholders to improve corporate governance, management practice, and internal control systems, leading to higher operational efficiency (Barth et al. 2013; Johnson and Greening 1999; Parmigiana et al. 2011). We thus develop our third hypothesis that CDS trading leads to higher operational efficiency through enhanced corporate monitoring, governance, and control by stakeholders (H2b). Figure 2 shows the theoretical framework of the current research.

> H2b: The inception of CDS leads to the higher operational efficiency of the underlying firm mediating through corporate monitoring, governance, and control.

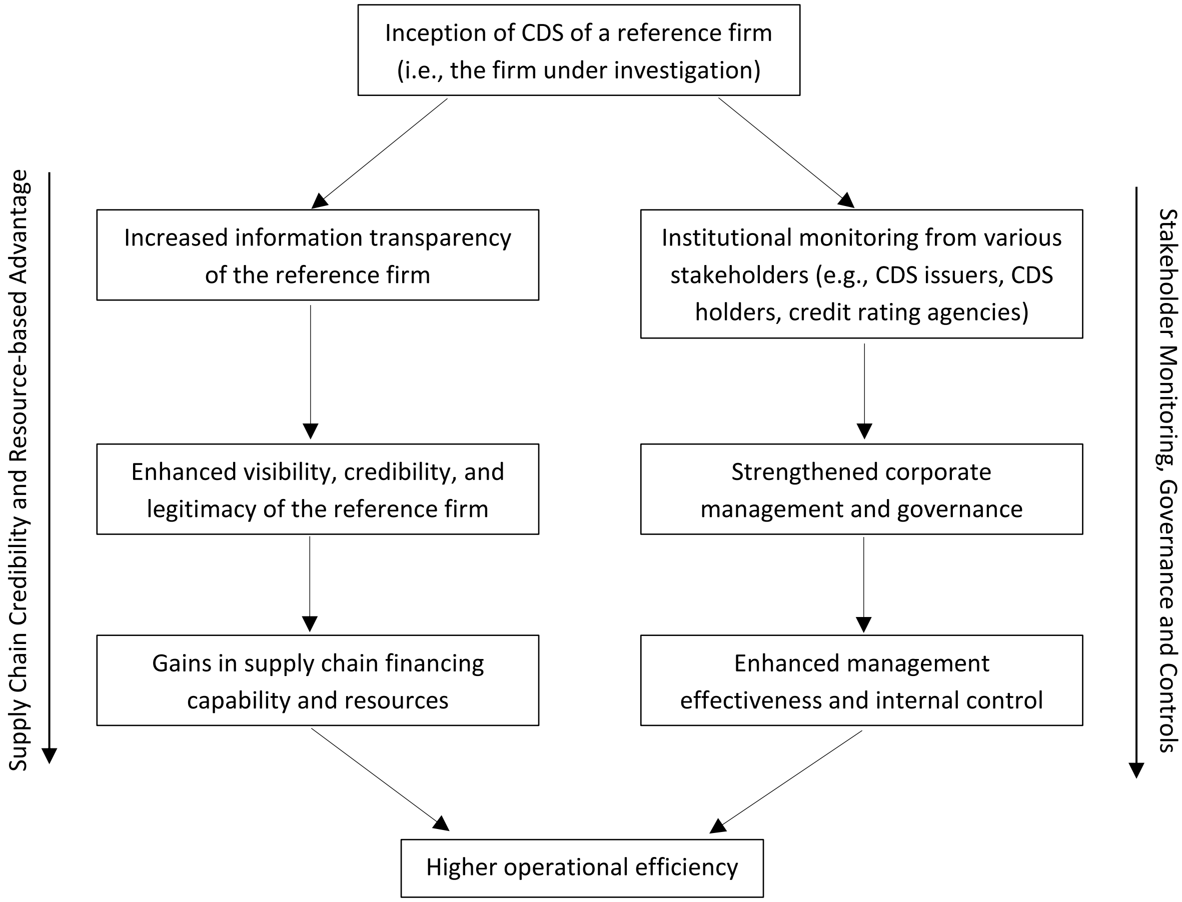

Figure 2. Theoretical Framework

3. Data and Measures

3.1. Data

We collect firms' characteristic data and CDS trading data from several sources; these data reflect the period 1997–2014. First, we obtain the firm-level accounting data from the Compustat database. Next, we obtain the CDS data from "GFI Group," a leading CDS market interdealer broker, and these data cover the North American single-name CDS trading information from 1997–2009. To obtain our final sample, we merged the aforementioned data and dropped observations from financial and utility industries as well as observations with missing control variables. Table 1 summarizes the sample selection process. In sum, our final sample includes a total of 20,289 firm-year observations, representing 3,442 unique firms, 265 of which are CDS active firms initiated in the period 1997–2008.

Table 1. Sample Selection Process

Sample Selection

Number of CDS initiation firms from 1997 to 2009 reported by "GFI Group"	**796**
Merging CDS data & Accounting data:	
Number of firm-year observations with two-year consecutive operational efficiency data from 1997 to 2014	119,245
Less: Number of firm-year observations for firms in financial and utility industries	(24,738)
Less: Number of firm-year observations with missing control variables (531 CDS firms are not matched)	(74,218)
Final Sample (Number of firm-year observations from 1997 to 2014)	**20,289**
Observations for 265 firms with CDS from 1997 to 2014	2,749
Observations for firms without CDS from 1997 to 2014	17,540

Table 2. Sample Distribution (Sample: 1997–2014 without financial & utility industry)

Panel A CDS firms distribution by initiation year

CDS Initial Year	N	Ratio of total CDS firms	Aggregate ratio
1997	16	6.04%	6.04%
1998	26	9.81%	15.85%
1999	13	4.91%	20.75%
2000	37	13.96%	34.72%
2001	45	16.98%	51.70%
2002	60	22.64%	74.34%
2003	23	8.68%	83.02%
2004	15	5.66%	88.68%
2005	14	5.28%	93.96%
2006	12	4.53%	98.49%
2007	2	0.75%	99.25%
2008	2	0.75%	100.00%
Total	265	100.00%	100.00%

Panel B Sample distribution by year

Fiscal Year	Total firms	CDS active firms	CDS firms ratio
1997	833	11	1.32%
1998	883	23	2.60%
1999	967	29	3.00%
2000	1,059	54	5.10%
2001	1,221	89	7.29%
2002	1,260	133	10.60%
2003	1,350	158	11.70%
2004	1,350	169	12.50%
2005	1,311	168	12.80%
2006	1,256	165	13.10%
2007	1,207	162	13.40%
2008	1,230	170	13.80%
2009	1,197	160	13.40%
2010	1,123	154	13.70%
2011	1,057	156	14.80%
2012	1,018	147	14.40%
2013	986	144	14.60%
2014	981	140	14.30%
Total	20,289	2,232	11.00%

In Panel A of Table 2, we report the CDS firms that we include in our final sample by initiation year. We use the first CDS trading date as the CDS initiation date. If the underlying firm's fiscal year-end date is after the CDS initiation date, then, the fiscal year is regarded as a CDS active year. Accordingly, we treat the first CDS active year of the stock as the initiation year. The number of CDS introduced firms in each year ranges from 2 firms in 2007 and 2008 to 60 firms in 2002. In Panel B of Table 2, we report the year-by-year sample coverage, which includes the total firms and CDS active firms each year. The number of firms with CDSs in our sample ranges between 11 and 170,[3] with an average CDS firm ratio between 1.32% and 14.80%. We report the industry distribution (2-digit SIC codes) of CDS firms and the final sample in the Online Appendix (Table OA2).

3.2 Variables

Our key variables are CDS trading and operational efficiency. CDS_{it} is a dummy variable that represents whether CDS is available to firm *i* at time t. If the firm is in and after the inception of CDS trading, then, it equals 1; otherwise, 0. To measure operational efficiency, we followed the Stochastic Frontier Estimation (SFE) methodology (Battese and Coelli 1988; Dutta et al. 2005; Lam et al. 2016; Li et al. 2010; Yiu et al. 2020). As for the SFE model itself, the number of employees, the cost of goods sold, and capital expenditure are all operational resources; operating income is operational output[4]. We first developed a stochastic production function model to model the relation between the resources and output of the firms as follows:

$$ln\ (Operating\ Income)_{ijt} = b_0 + b_1 ln(Number\ of\ Employees)_{ijt} +$$
$$b_2 ln(Cost\ of\ Goods\ Sold)_{ijt} + b_3 ln(Capital\ Expenditure)_{ijt} + v_{ijt} - h_{ijt}. \quad (1)$$

where v_{ijt} is the random error based on stochastic modeling, and h_{ijt} represents the loss of efficiency by firm *i* relative to industry *j* in year *t* (estimates based on 2-digit SIC codes). When estimating the loss of efficiency, we first follow Battese and Coelli (1988) and adopt a methodology on the basis of the panel data structure model. The loss of efficiency (h_{ijt}) has a half-normal distribution. To increase the robustness, we follow Jondrow et al. (1982) to obtain our second measure by estimating the loss of efficiency on the basis of the cross-sectional model in which h_{ijt} has a half-normal distribution. h_{ijt} ranges from 0 to 1, and a high value indicates a high loss in efficiency (i.e., low operational efficiency). Accordingly, we measured the operational efficiency of a firm relative to its industry by revising the value of h_{ijt}:

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[3] The number of CDS initiation firms and CDS active firms are different (e.g., 16 firms were initiated CDS trading in 1997 while 11 CDS active firms exist in 1997) because not every firm has corresponding accounting data in every year in our sample period (e.g., some firms have no corresponding accounting data in their first CDS trading year).
[4] Further information about the SFE model is provided in Online Appendix (OA-1).

$$Operational\ Efficiency_{ijt} = 1 - h_{ijt}.(2)$$

Correspondingly, we have two operational efficiency measures: *OPERATIONAL EFFICIENCY* $1_{i,t}$ following Battese and Coelli (1988) and *OPERATIONAL EFFICIENCY* $2_{i,t}$ following Jondrow et al. (1982).

Following prior studies on operational efficiency (Wu et al. 2010; Bellamy et al. 2014; Kortmann et al. 2014; Lam et al. 2016), we include firm size (*FIRM SIZE,* which represents the natural logarithm of a firm's total assets), firm profitability (*FIRM PROFITABILITY,* which represents a firm's return on assets), firm leverage (*FIRM LEVERAGE*, which represents the firm's total liability divided by total assets), firm age (*FIRM AGE,* which represents the natural logarithm of the number of years since a firm's IPO[5]), firm advertising expense (*FIRM ADVERTISING EXPENSE*, which represents a firm's advertising expenses divided by sales), market-to-book ratio (*MARKET-TO-BOOK*, which is a firm's market value divided by its book value), cash holdings (*CASH*, measured as a firm's cash divided by total assets), retained earnings (*RETAINED EARNINGS*, which is a firm's retained earnings divided by total assets), tangible assets (*PPENT*, measured as a firm's property, plant, and equipment divided by total assets), working capital (*WORKING CAPITAL*, which equals a firm's working capital divided by total assets), and institutional governance (*INSTITUTIONAL OWNERSHIP DUMMY*, a dummy variable that equals 1 if a firm has an institutional stockholder; otherwise, 0) as controls. Additionally, we control credit rating (*CREDIT RATING DUMMY*, a dummy variable that equals 1 if a firm has a Standard & Poor's debt rating; otherwise, 0) and investment grades (*INVESTMENT GRADE DUMMY,* dummies assigned to each investment grade level) to capture firms' credit risk.

Table 3 presents the summary statistics for our final sample.[6] We winsorize all variables at the 1% and 99% levels. On average, 11% of our firm-year observations are CDS active firm-years. In terms of the mediating variables, the average (median) accounts payable of firms is 18.6% (11.8%) of their cost of goods sold. On average, institutional investors hold 33.9% of firms' shares, and the median ratio is 19.1%. As for the firm's characteristics, the mean (median) value of firm size in terms of total assets is 5.606 (5.577) in natural logarithm, which is 272.05 million (264.28 million) in actual value. Furthermore, the average (median) profitability in terms of ROA is -9.7% (3%), the average (median) firm age since IPO is 2.605 (2.639) in natural logarithm, which is 13.53 years (14.00 years) in actual value, and the average (median) firm advertising expense is 3.5% (1.4%) of firm's sales. The mean (median) value of the firm's market-to-book ratio is 2.871 (1.927). About 26.8% of our final observations have a Standard & Poor's rating for their debt. On average, the firm's cash holding accounted for 19.8% of its total assets, retained earnings accounted for -130.9%, and working capital accounted for 21.2%. 22.9% of total assets are tangible assets.

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[5] For firms without IPO date, we use the date they first appeared in CRSP as the IPO date.

[6] The definitions of variable are shown in the Online Appendix (Table OA1).

67.2% of our final observations have institutional stockholders. Correlations among all the variables are shown in the Online Appendix (Table OA3).

Table 3. Summary Statistics

Variable	N	Mean	SD	p50	p25	p75	Min	Max
CDS_{it}	20,289	0.110	0.313	0	0	0	0	1
OPERATIONAL EFFICIENCY 1$_{i,t}$	20,289	0.520	0.263	0.523	0.338	0.682	0.008	1.000
OPERATIONAL EFFICIENCY 2$_{i,t}$	20,289	0.496	0.267	0.487	0.305	0.658	0.007	1.000
FIRM SIZE$_{i,t}$	20,289	5.606	2.422	5.577	3.812	7.285	0.542	11.380
FIRM PROFITABILITY$_{i,t}$	20,289	-0.097	0.485	0.030	-0.063	0.080	-3.376	0.334
FIRM LEVERAGE$_{i,t}$	20,289	0.568	0.512	0.482	0.302	0.674	0.066	4.131
FIRM AGE$_{i,t}$	20,289	2.605	0.825	2.639	2.079	3.178	0.693	4.394
FIRM ADVERTISING EXPENSE$_{i,t}$	20,289	0.035	0.058	0.014	0.005	0.038	0.000	0.384
MARKET-TO-BOOK$_{i,t}$	20,289	2.871	6.076	1.927	1.003	3.608	-21.520	37.020
CREDIT RATING DUMMY$_{i,t}$	20,289	0.268	0.443	0	0	1	0	1
CASH$_{i,t}$	20,289	0.198	0.200	0.127	0.040	0.295	0.000	0.824
RETAINED EARNINGS$_{i,t}$	20,289	-1.309	5.231	0.066	-0.565	0.343	-39.050	0.976
PPENT$_{i,t}$	20,289	0.229	0.202	0.165	0.073	0.322	0.005	0.839
WOKRING CAPITAL$_{i,t}$	20,289	0.212	0.381	0.233	0.058	0.426	-2.110	0.829
INSTITUTIONAL OWNERSHIP DUMMY$_{i,t}$	20,289	0.672	0.470	1	0	1	0	1
TRADE CREDIT$_{i,t}$	20,289	0.186	0.279	0.118	0.071	0.188	0.009	2.170
INSTITUTIONAL OWNERSHIP$_{i,t}$	20,289	0.339	0.359	0.191	0	0.688	0	1

4. Empirical Results

4.1. Baseline Analysis

In this section, we examine the impact of financial innovation (i.e., the availability of CDS trades to lenders) on a focal firm's operational efficiency. We estimate the following regression model:

$$Operational\ Efficiency_{i,t+1} = a_0 + \beta_1 CDS_{it} + a_1\ Firm\ Size_{it} + a_2 Firm\ Profitablity_{it} + a_3 Firm\ Leverage_{it} + a_4 Firm\ Age_{it} + a_5 Firm\ Advertising\ Expense_{it} + \alpha_6 Market-to-Book_{i,t} + \alpha_7 Credit\ Rating\ Dummy_{i,t} + \alpha_8 Cash_{i,t} + \alpha_9 Retained\ Earnings_{i,t} + \alpha_{10} PPENT_{i,t} + \alpha_{11} Working\ Capital_{i,t} + \alpha_{12} Institutional\ Ownership\ Dummy_{i,t} + Control\ (Investment\ Grade, Firm, Year) + \varepsilon_{it}. \qquad (3)$$

Our dependent variable is $Operational\ Efficiency_{i,t+1}$, which is operational efficiency for firm i in year $t + 1$. Considering that it takes time for supply chain partners, the business community, and other stakeholders to pay attention to the CDS initiation firms and then take effect on firms' operational efficiency by providing additional financing and monitoring, our dependent variable is lagged in one year.[7] Our main

[7] We also conduct additional tests to provide supports for the lagged effects in Section 4.5.1.

independent variable is CDS_{it}, which is a dummy variable indicating whether the CDS is available for firm i at time t. Given that large firms are generally more efficient due to their economies of scale, we include firm size as a control and operationalize it by taking the natural logarithm of firm total assets (Bardhan et al. 2013; Hendricks et al. 2009). Considering that it is highly related to operational efficiency, we use firm profitability as a control and operationalize it as a firm's net income scaled by total assets (Chizema et al. 2015; Mukherji et al. 2011). We also control for firm leverage as a firm's total liability divided by total assets, control firm age as the natural logarithm of years since a firm was listed publicly (Carter and Lynch 2001; Wang et al. 2008), control for firm advertising expense by scaling a firm's spending on advertising by firm sales (Lou 2014; Pirinsky and Wang 2006), and control for firm's market-to-book ratio by dividing a firm's market value by its book value. Then we use the firm's cash holding, retained earnings, tangible assets, and working capital to control for the firm's operational resources. Besides, we add an institutional ownership dummy to control for firm's institutional governance. Additionally, we control for the firm's credit rating, which is a dummy variable that equals 1 if a firm has a Standard & Poor's debt rating, and investment grades to capture firms' credit risk. To control for unobservable time and firm-specific effects, we also add the year- and firm-fixed effects in our regression.

We present our baseline estimation results in Table 4. To address the issue that the model may fail to meet standard regression assumptions (e.g., clustering, heteroscedasticity), we report the robust t and bootstrap z statistics, and all the standard errors are clustered at the firm level. In columns 3 (robust t statistics) and 5 (bootstrap z statistics), we find that the coefficients on *CDS* are significantly positive, suggesting that the introduction of CDS can increase a focal firm's operational efficiency, which is consistent with our *Hypothesis 1*. Our results are robust to our other operational efficiency measures. Economically, the introduction of CDS could help firms increase their operational efficiency by 7.31% (7.66%) on average, measured by $Operational\ Efficiency$ 1 ($Operational\ Efficiency$ 2).[8]

[8] The percentage is calculated by dividing the CDS's coefficients by the mean of Operational Efficiency. For $Operational\ Efficiency$ 1, 0.038/0.520=7.31%, and for $Operational\ Efficiency$ 2, 0.038/0.496=7.66%.

Table 4. Baseline Analysis: The Impact of the availability of CDS on Operational Efficiency

	(1) *OPERATIONAL EFFICIENCY* $1_{i,t+1}$	(2) *OPERATIONAL EFFICIENCY* $2_{i,t+1}$	(3) *OPERATIONAL EFFICIENCY* $1_{i,t+1}$	(4) *OPERATIONAL EFFICIENCY* $2_{i,t+1}$	(5) *OPERATIONAL EFFICIENCY* $1_{i,t+1}$	(6) *OPERATIONAL EFFICIENCY* $2_{i,t+1}$
CDS_{it}	**0.034****	**0.034****	**0.038****	**0.038****	**0.038****	**0.038****
	(2.053)	**(2.003)**	**(2.241)**	**(2.195)**	**(2.282)**	**(2.234)**
FIRM SIZE$_{i,t}$			0.001	0.001	0.001	0.001
			(0.210)	(0.184)	(0.228)	(0.255)
FIRM PROFITABILITY$_{i,t}$			-0.004	-0.004	-0.004	-0.004
			(-0.615)	(-0.621)	(-0.590)	(-0.589)
FIRM LEVERAGE$_{i,t}$			-0.006	-0.006	-0.006	-0.006
			(-0.638)	(-0.598)	(-0.480)	(-0.568)
FIRM AGE$_{i,t}$			0.009	0.009	0.009	0.009
			(0.739)	(0.722)	(0.723)	(0.855)
FIRM ADVERTISING EXPENSE$_{i,t}$			-0.028	-0.023	-0.028	-0.023
			(-0.454)	(-0.371)	(-0.383)	(-0.318)
MARKET-TO-BOOK$_{i,t}$			-0.000	-0.000	-0.000	-0.000
			(-0.996)	(-0.950)	(-1.025)	(-1.176)
CREDIT RATING DUMMY$_{i,t}$			-0.044	-0.044	-0.044	-0.044
			(-0.617)	(-0.573)	(-0.517)	(-0.606)
CASH$_{i,t}$			0.002	0.004	0.002	0.004
			(0.073)	(0.153)	(0.075)	(0.140)
RETAINED EARNINGS$_{i,t}$			-0.001	-0.001	-0.001	-0.001
			(-0.806)	(-0.740)	(-0.746)	(-0.684)
PPENT$_{i,t}$			-0.007	-0.005	-0.007	-0.005
			(-0.193)	(-0.140)	(-0.188)	(-0.171)
WOKRING CAPITAL$_{i,t}$			0.001	0.001	0.001	0.001
			(0.037)	(0.048)	(0.030)	(0.050)
INSTITUTIONAL OWNERSHIP DUMMY$_{i,t}$			-0.011	-0.011	-0.011	-0.011
			(-1.163)	(-1.099)	(-1.273)	(-1.280)
INVESTMENT GRADE DUMMIES$_{i,t}$			Yes	Yes	Yes	Yes
Constant	0.531***	0.506***	0.594***	0.568***	0.594***	0.568***
	(56.121)	(52.669)	(5.522)	(5.160)	(4.419)	(6.631)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,289	20,289	20,289	20,289	20,289	20,289
R2	0.002	0.002	0.004	0.004	0.004	0.004

Notes. Robust *t* statistics in parentheses in columns (1)–(4) and bootstrap z statistics in parentheses in columns (5)–(6). All standard errors are clustered at firm level. R2 is based on fixed-effects (within) regression.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2. Endogeneity Concerns of the Availability of CDS

As we discussed earlier, the availability of CDS could be endogenously determined. In turn, firms with higher operational efficiency may perform better and experience higher growth opportunities; thus, such firms are more likely to have CDS based on their credit events. We employ various identification strategies to address this concern: (i) a Heckman-type model, (ii) a regression based on the matched sample, and (iii) a two-stage regression with an instrumental variable.

4.2.1. Heckman-Type Model

Firms are not randomly selected into the CDS trading market, thereby raising one endogeneity issue on sample selection bias. Knowing the underlying selection process regarding CDS availability, we can use the Heckman-type model to alleviate the concern about sample selection bias (Kumar et al. 2018a). First, we model the possibility of CDS trading for a firm using the selection equation. Then, we estimate equation (3) by controlling the CDS trading probability. The selection equation is given as follows:

$$\begin{gathered}\text{Probit}\left(\text{CDS}_{i,t}=1\right)=\alpha_0+\alpha_1 Lender\ Tier\ 1\ Capital_{i,t}+\alpha_2 Firm\ Size_{i,t-1}+\\ \alpha_3 Firm\ Profitablity_{i,t-1}+\alpha_4 Firm\ Leverage_{i,t-1}+\alpha_5 Firm\ Age_{i,t-1}+\\ \alpha_6 Firm\ Advertising\ Expense_{i,t-1}+\alpha_7 Market-to-Book_{i,t-1}+\alpha_8 Credit\ Rating\ Dummy_{i,t-1}+\\ \alpha_9 Cash_{i,t-1}+\alpha_{10} Retained\ Earnings_{i,t-1}+\alpha_{11} PPENT_{i,t-1}+\alpha_{12} Working\ Capital_{i,t-1}+\\ \alpha_{13} Institutional\ Ownership\ Dummy_{i,t-1}+Control\ (Investment\ Grade, Industry, Year).\end{gathered} \quad (4)$$

where $Lender\ Tier\ 1\ Capital$ is the average of the Tier 1 capital level across the banks that have served as lenders or bond underwriters for firm *i* over the previous five years. We identify the lenders and bond underwriters for firms on the basis of DealScan data and FISD data. Then we obtain Tier 1 Capital information of these lenders and bond underwriters from the Bank Regulatory Database and Compustat Bank file. As we mentioned earlier, the lenders (e.g., banks) buy CDS from CDS sellers (e.g., insurance companies, hedge funds) to hedge against the credit risk of underlying assets. Usually, the lenders initiate CDS trading on the firm’s debt, and Tier 1 capital level could explain the hedging needs of banks. Tier 1 capital is an important measure to reflect a bank’s financial strength. A bank in a good financial situation (with a high Tier 1 capital level) would have low needs to hedge against credit risk. Thus, a firm with a higher Lender Tier 1 Capital will have a lower probability to have CDS trading on its debt. At the same time, Tier 1 capital is a measure to reflect lenders’ or bond underwriters’ financial strength rather than firms’ financial strength, and it should not directly affect firms’ operational efficiency or through other channels to affect firms’ operational efficiency. Therefore, Lender Tier 1 Capital is likely to meet the exclusion requirement, and we use it as the exogenous variable in the selection model (Subrahmanyam et al. 2014).

When estimating the selection model, we use data from 1997 to the first year of CDS trading for

CDS active firms and all observations in our sample for non-CDS firms. Industry (2-digit SIC codes) and year-fixed effects are controlled. Results of the selection model are shown in the Online Appendix (Table OA4). After obtaining the inverse mills ratio (IMR) based on the selection model, we add the IMR in the baseline regression model (equation 3) and re-estimate the effect of CDS on the focal firm's operational efficiency after correcting the sample selection issue.

We present the estimation results of the Heckman correction (second-stage) in Table 5. These results show that the coefficients of CDS are all significantly positive. And after addressing the sample selection bias issue, the increased level of operational efficiency due to the inception of CDS enlarges, which is 13.07% (14.31%) on average based on *Operational Efficiency 1* (*Operational Efficiency 2*).

Table 5. Results of Heckman Correction

	(1) *OPERATIONAL EFFICIENCY 1$_{i,t+1}$*	(2) *OPERATIONAL EFFICIENCY 2$_{i,t+1}$*	(3) *OPERATIONAL EFFICIENCY 1$_{i,t+1}$*	(4) *OPERATIONAL EFFICIENCY 2$_{i,t+1}$*
$\boldsymbol{CDS_{i,t}}$	**0.068****	**0.071****	**0.068****	**0.071****
	(2.045)	**(2.080)**	**(2.061)**	**(2.140)**
IMR	**-0.013**	**-0.014**	**-0.013**	**-0.014**
	(-0.611)	**(-0.665)**	**(-0.586)**	**(-0.698)**
FIRM SIZE$_{i,t}$	-0.015	-0.015	-0.015	-0.015
	(-1.394)	(-1.389)	(-1.442)	(-1.318)
FIRM PROFITABILITY$_{i,t}$	-0.018*	-0.018*	-0.018*	-0.018*
	(-1.900)	(-1.880)	(-1.780)	(-1.710)
FIRM LEVERAGE$_{i,t}$	0.002	0.002	0.002	0.002
	(0.593)	(0.627)	(0.137)	(0.171)
FIRM AGE$_{i,t}$	0.017	0.017	0.017	0.017
	(0.857)	(0.836)	(0.776)	(0.738)
FIRM ADVERTISING EXPENSE$_{i,t}$	0.005	0.033	0.005	0.033
	(0.032)	(0.182)	(0.027)	(0.192)
MARKET-TO-BOOK$_{i,t}$	-0.000	-0.000	-0.000	-0.000
	(-0.965)	(-0.799)	(-0.553)	(-0.495)
CREDIT RATING DUMMY$_{i,t}$	-0.087	-0.091	-0.087	-0.091
	(-1.164)	(-1.130)	(-1.022)	(-0.889)
CASH$_{i,t}$	-0.003	-0.001	-0.003	-0.001
	(-0.060)	(-0.027)	(-0.057)	(-0.022)
RETAINED EARNINGS$_{i,t}$	0.004*	0.004*	0.004*	0.004
	(1.902)	(1.872)	(1.852)	(1.351)
PPENT$_{i,t}$	-0.121**	-0.119*	-0.121**	-0.119**
	(-1.977)	(-1.896)	(-1.962)	(-2.464)
WOKRING CAPITAL$_{i,t}$	-0.017	-0.017	-0.017	-0.017
	(-1.021)	(-0.980)	(-0.820)	(-0.996)
INSTITUTIONAL OWNERSHIP DUMMY$_{i,t}$	-0.017	-0.016	-0.017	-0.016
	(-1.090)	(-1.024)	(-1.379)	(-1.298)
INVESTMENT GRADE DUMMIES$_{i,t}$	Yes	Yes	Yes	Yes
Constant	0.749***	0.732***	0.749***	0.732***

	(4.998)	(4.767)	(4.193)	(4.023)
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Observations	9376	9376	9376	9376
R2	0.010	0.010	0.010	0.010

Notes. Robust *t* statistics in parentheses in columns (1)–(2), and bootstrap z statistics in parentheses in columns (3)–(4). All standard errors are clustered at firm level. R2 is based on fixed-effects (within) regression. * *p* < 0.1, ** *p* < 0.05, *** *p* < 0.01.

4.2.2. Regression Results based on PSM Sample

One concern of the Heckman-type model regression results is that we cannot model the selection process with high accuracy and comprehensiveness. Not all factors that contribute to CDS trading can be measured in the selection equation. Omitted variables could exist which could simultaneously affect CDS trading probability and the firm's operational efficiency. To address this issue and alleviate the concerns about endogeneity problems, we will consider different matching techniques in the next two parts. The first matching technique we consider is the PSM method (Goh et al. 2013; Chen et al. 2021; Petryk et al. 2022). Following Li (2016), Bapna et al. (2019), Khurana et al. (2019), and Wang et al. (2022), we first use PSM to create a "proper" control group for the treated firms. The PSM matching process is as follows. Given we focus on predicting the likelihood of CDS trade initiation, we follow Subrahmanyam et al. (2014) and Chang et al. (2019) and only keep the observations one year before CDS initiation for CDS active firms and all the observations from 1996 to 2008 for non-CDS firms. Then, we randomly sort all firms and run a logit model, controlling for the firm's observable characteristics that could affect CDS trading in the one year before CDS initiation on the right-hand side, to derive the propensity scores. By matching each treated firm with one control firm with the closest propensity score, we obtain the PSM-matched firms. The logit regression model is as follows:

$$\begin{gathered}\text{Logit}(\text{CDS}_{it}=1)=\alpha_0+\alpha_1 Firm\ Size_{i,t-1}+\alpha_2 Firm\ Profitablity_{i,t-1}+\alpha_3 Firm\ Leverage_{i,t-1}+\\ \alpha_4 Firm\ Age_{i,t-1}+\alpha_5 Firm\ Advertising\ Expense_{i,t-1}+\alpha_6 Market-to-Book_{i,t-1}+\\ \alpha_7 Credit\ Rating\ Dummy_{i,t-1}+\alpha_8 Cash_{i,t-1}+\alpha_9 Retained\ Earnings_{i,t-1}+\alpha_{10} PPENT_{i,t-1}+\\ \alpha_{11} Working\ Capital_{i,t-1}+\alpha_{12} Institutional\ Ownership\ Dummy_{i,t-1}+\\ Control\ (Investment\ Grade, Industry, Year). \qquad (5)\end{gathered}$$

Next, we obtain all the observations from 1997 to 2014 for the PSM-matched firms and use the new sample created to conduct the PSM-difference-in-differences (DiD) test by re-estimating our regression equation (3) (Cheng et al. 2020; Pan and Qiu 2021; Fan et al. 2022; Kumar et al. 2022a, b).[9] The

[9] For our setting, a typical DiD regression model should be $Operational\ Efficiency_{i,t+1}=a_0+\beta_1 CDS\ Firm_i\times Post_{it}+\beta_2 CDS\ Firm_i+\beta_3 Post_t+a_i Controls_{i,t}+\varepsilon_{it}$, where $CDS\ Firm_i$ is the treatment dummy that equals 1 if a firm has CDS trading on its debt during our sample period; otherwise, 0. $Post_{it}$ is the post-treatment dummy that equals 1 in the post-CDS period; otherwise, 0. When year and firm fixed effects are controlled, including $CDS\ Firm_i$

comparison of the summary statistics of the treatment group and control group before and after PSM are shown in the Online Appendix (Table OA5). Table 6 reports our basic findings, and the results are consistent with those in our baseline model. In addition, the effect of CDS on a firm's operational efficiency becomes larger after addressing the omitted variables concern, which is 10.58% (11.29%) on average based on *Operational Efficiency 1* (*Operational Efficiency 2*), compared with our baseline results.

Table 6. Test on PSM-Matched Sample

	(1) *OPERATIONAL EFFICIENCY* $1_{i,t+1}$	(2) *OPERATIONAL EFFICIENCY* $2_{i,t+1}$	(3) *OPERATIONAL EFFICIENCY* $1_{i,t+1}$	(4) *OPERATIONAL EFFICIENCY* $2_{i,t+1}$
$\boldsymbol{CDS_{it}}$	**0.055****	**0.056****	**0.055*****	**0.056*****
	(2.580)	**(2.550)**	**(3.145)**	**(3.175)**
FIRM SIZE$_{i,t}$	-0.002	-0.002	-0.002	-0.002
	(-0.155)	(-0.115)	(-0.191)	(-0.097)
FIRM PROFITABILITY$_{i,t}$	-0.147*	-0.140*	-0.147***	-0.140
	(-1.873)	(-1.746)	(-3.168)	(-1.621)
FIRM LEVERAGE$_{i,t}$	-0.010	-0.009	-0.010	-0.009
	(-0.151)	(-0.134)	(-0.164)	(-0.132)
FIRM AGE$_{i,t}$	0.020	0.017	0.020	0.017
	(0.864)	(0.732)	(0.871)	(0.870)
FIRM ADVERTISING	-1.021**	-1.030**	-1.021***	-1.030**
EXPENSE$_{i,t}$	(-2.404)	(-2.370)	(-3.326)	(-2.564)
MARKET-TO-BOOK$_{i,t}$	-0.000	-0.000	-0.000	-0.000
	(-0.223)	(-0.255)	(-0.251)	(-0.245)
CREDIT RATING DUMMY$_{i,t}$	0.029	0.030	0.029	0.030
	(0.282)	(0.278)	(0.421)	(0.258)
CASH$_{i,t}$	0.248***	0.262***	0.248**	0.262**
	(2.643)	(2.721)	(2.262)	(2.529)
RETAINED EARNINGS$_{i,t}$	-0.006	-0.004	-0.006	-0.004
	(-0.173)	(-0.110)	(-0.193)	(-0.090)
PPENT$_{i,t}$	-0.152	-0.145	-0.152*	-0.145
	(-1.281)	(-1.195)	(-1.833)	(-1.003)
WOKRING CAPITAL$_{i,t}$	0.007	-0.003	0.007	-0.003
	(0.085)	(-0.031)	(0.075)	(-0.024)
INSTITUTIONAL	0.024	0.025	0.024	0.025
OWNERSHIP DUMMY$_{i,t}$	(1.071)	(1.095)	(1.043)	(0.985)
INVESTMENT GRADE DUMMIES$_{i,t}$	Yes	Yes	Yes	Yes
Constant	0.626***	0.602***	0.626***	0.602***
	(3.155)	(2.955)	(4.181)	(2.848)
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Observations	3362	3362	3362	3362
R2	0.041	0.042	0.041	0.042

Notes: Robust t statistics in parentheses in columns (1)–(2), and bootstrap z statistics in parentheses in columns (3)–(4). All standard errors are clustered at firm level. R2 is based on fixed-effects (within) regression. * p < 0.1, ** p < 0.05,

and $Post_{it}$ in the model is unnecessary, and the DiD model is then reduced to model (3) where $CDS_{i,t} = CDS\ Firm_{\,i} \times Post_{it}$.

*** p < 0.01.

4.2.3. Regression Results based on CEM Sample

PSM is an approximate matching approach. To increase the robustness of our matched sample, we will use an exact matching method in this part, namely, CEM, to construct our matched sample. As noted by previous studies (Blackwell et al. 2009; Iacus et al. 2012; Chen et al. 2022), CEM is faster, easier to use, requires fewer assumptions, robust to measurement error, and strictly bounds both the degree of model dependence and the average treatment-effect estimation error through ex-ante user choice. To implement the CEM method, we need to first coarsen our data, determine an exact match on these coarsened data, and then conduct our analysis on the un-coarsened, matched data.

Our CEM matching process is as follows. Similar to the PSM matching, we only keep the observations one year before CDS initiation for CDS active firms and all the observations from 1996 to 2008 for non-CDS firms. Then, we define the cut-points for each continuous control variable and coarsen our data on the basis of the dummy control variables and cut-points of continuous control variables in equation (5). Then, we create one stratum per unique observation of coarsened data and assign these strata to the original (un-coarsened) data and match treated firms with control firms within each stratum. We also use the k2k option to ensure that we have the same number of CDS and non-CDS firms. Our matched sample includes all the observations from 1997 to 2014 of the matched firms. The univariate imbalance for each control variable after CEM is shown in the Online Appendix (Table OA6).

Next, we obtain all the observations from 1997 to 2014 for the CEM-matched firms and use the new sample to re-estimate our regression equation (3), and we present our results in Table 7. Our basic findings are consistent with those in our baseline model. And the increased level of operational efficiency due to the inception of CDS also enlarges, which is 10.19% (10.89%) on average based on *Operational Efficiency 1* (*Operational Efficiency 2*).

Table 7. Regression Results based on CEM-Matched Sample

	(1) *OPERATIONAL EFFICIENCY* $1_{i,t+1}$	(2) *OPERATIONAL EFFICIENCY* $2_{i,t+1}$	(3) *OPERATIONAL EFFICIENCY* $1_{i,t+1}$	(4) *OPERATIONAL EFFICIENCY* $2_{i,t+1}$
$\boldsymbol{CDS_{it}}$	**0.053****	**0.054****	**0.053****	**0.054****
	(2.232)	**(2.169)**	**(2.219)**	**(2.335)**
Controls	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Observations	2509	2509	2509	2509
R2	0.052	0.052	0.052	0.052

Notes: Robust t statistics in parentheses in columns (1)–(2), Bootstrap z statistics in parentheses in columns (3)–

(4). Controls are the same as in baseline regression. All standard errors are clustered at the firm level. R2 is based on fixed-effects (within) regression. * p < 0.1, ** p < 0.05, *** p < 0.01.

4.2.4. Instrumental Variable Approach

Although we have conducted the analysis on the basis of the Heckman correction model and PSM/CEM matched sample to alleviate the concerns about sample selection bias and omitted variables, characteristics may exist and affect CDS trading probability and the firm's operational efficiency. However, we cannot directly control this possible scenario in our model. In this part, we conduct a two-stage regression using Instrumental Variable (IV) to address the potential endogeneity issue further. Following Subrahmanyam et al. (2014), we implement the Lender Tier 1 Capital as the IV defined as the average of the Tier 1 capital level across the banks that have served as lenders or bond underwriters for a particular firm over the previous five years. As mentioned in the Heckman selection model, banks' Tier 1 capital should negatively affect the probability of CDS trading on a firm's debt and are less likely to affect a firm's operational efficiency directly or through other channels. To correct the standard errors, we run the regression on the basis of the GMM method. Table 8 reports the empirical results. The coefficients of CDS are positive and marginally significant (the coefficients are significant at the 5% level in the one-tailed test), demonstrating the consistency of the findings after addressing the endogeneity. And the increased level of operational efficiency due to the inception of CDS becomes even larger, which is 23.46% (23.99%) on average based on *Operational Efficiency 1* (*Operational Efficiency 2*) since the IV approach can address both observed and unobserved confounders.

Besides, to further alleviate the concerns of endogeneity issues, we follow the procedures in Wooldridge (2010) to merge Heckman correction and two-stage least squares (2SLS) models, which combine selection and endogenous treatment methods together. The results are shown in Online Appendix (Table OA7), and the coefficients of CDS are all significantly positive after controlling for selection and endogenous issues together.

Table 8. Instrumental Variable GMM Regression: *Lender Tier 1 Capital*

	(1) *OPERATIONAL EFFICIENCY $1_{i,t+1}$*	(2) *OPERATIONAL EFFICIENCY $2_{i,t+1}$*
$\widehat{CDS}_{it}$	**0.122***	**0.119***
	(1.916)	**(1.824)**
FIRM SIZE$_{i,t}$	-0.006	-0.006
	(-1.166)	(-1.122)
FIRM PROFITABILITY$_{i,t}$	-0.006	-0.005
	(-1.413)	(-1.307)
FIRM LEVERAGE$_{i,t}$	0.001	0.001
	(0.359)	(0.416)

FIRM AGE$_{i,t}$	-0.008	-0.007
	(-0.936)	(-0.809)
FIRM ADVERTISING EXPENSE$_{i,t}$	-0.010	-0.002
	(-0.088)	(-0.020)
MARKET-TO-BOOK$_{i,t}$	-0.000*	-0.000*
	(-1.687)	(-1.767)
CREDIT RATING DUMMY$_{i,t}$	0.036	0.025
	(0.673)	(0.453)
CASH$_{i,t}$	0.027	0.027
	(0.830)	(0.814)
RETAINED EARNINGS$_{i,t}$	0.003**	0.003**
	(2.043)	(2.000)
PPENT$_{i,t}$	-0.022	-0.023
	(-0.818)	(-0.814)
WOKRING CAPITAL$_{i,t}$	-0.019	-0.020
	(-0.954)	(-0.996)
INSTITUTIONAL OWNERSHIP DUMMY$_{i,t}$	-0.006	-0.006
	(-0.545)	(-0.549)
INVESTMENT GRADE DUMMIES$_{i,t}$	Yes	Yes
Year Fixed Effect	Yes	Yes
Firm Fixed Effect	Yes	Yes
Observations	9954	9954

Notes: Robust *t* statistics in parentheses in columns (1)-(2). All standard errors are clustered at firm level. R2 is not reported because "R2 has no statistical meaning in the context of 2SLS/IV" (Ref: https://www.stata.com/support/faqs/statistics/two-stage-least-squares/. Last accessed on September 5th, 2021). GMM results are obtained using command xtabond2 in STATA. Observations with missing *Lender Tier 1 Capital* are dropped. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3 One-Year around CDS Initiation Analysis

In addition to the endogeneity issues, there is another concern, which is that the main independent variable CDS in our regression models may change its value between 0 and 1, and back and forth for some firms. In other words, some treated firms may become untreated in some years, and then become treated in other years. This treatment switch may affect our estimation results. Due to the data limitation, we cannot solve this problem directly. However, we believe that the effect of this treatment switch on our estimation is little since most CDS are long-term with five-year the most typical maturity (Galil et al. 2014; Mengle 2007). Besides, since CDS trading can help improve firms' operational efficiency, then this treatment switch would bias our results downwards, meaning that the positive effect of CDS trading on operational efficiency would be more significant if we can rule out the treatment switch effect. What's more, we conduct an additional analysis that only employs the observations in one-year around CDS initiation based on the PSM-matched sample to address this issue. We believe that in such a short window, the treated firms would not switch between treatment and control groups. The results are shown in Online Appendix (Table OA8), showing the consistent results.

4.4 Mediating Factors

To further explore how CDS trading increases firms' operational efficiency, for example, in our theory and hypothesis, supply chain financing and corporate monitoring can be two possible mediating factors through which the firms' operational efficiency is improved when CDSs are present. Accordingly, we further examine the mediating effects of trade credit on supply chain finance and institutional ownership on corporate monitoring by utilizing the Sobel test (Sobel 1982; 1987; MacKinnon et al. 2000; Ding et al. 2021; Yan et al. 2022). The regression models of the mediation tests are as follows:

$$\begin{cases} Trade\ Credit_{i,t+1}(\text{Or } Insitutional\ Ownership_{i,t}) = \alpha_0 + \beta_1 CDS_{i,t} + a_i Controls_{i,t} + \varepsilon_{it} \\ Operational\ Efficiency_{i,t+1} = a_0 + \gamma_1 Trade\ Credit_{i,t+1}(\text{Or } Insitutional\ Ownership_{i,t}) \\ \qquad + \delta_1 CDS_{it} + a_i Controls_{i,t} + \varepsilon_{it}, \end{cases} \quad (6)$$

where $\beta_1 \times \gamma_1$ captures the total mediation effect (indirect effect), and δ_1 captures the direct effect of CDS trading on operational efficiency. If the mediation effect of one particular mediating factor occurs, then, $\beta_1 \times \gamma_1$ should be significant. Control variables are the same as in the baseline regression (equation [3]), and firm and year fixed effects are controlled.

Following Fisman and Love (2003), we use *Accounts Payable/Cost of Goods Sold* as the Trade Credit measure (*Trade Credit*[10]) and report our results in Panel A of Table 9. The results are based on the PSM matched sample. The empirical findings show that the introduction of CDS trading could significantly increase the trade credit (marginally significant in the two-tailed test and significant at the 5% level in the one-tailed test), which in turn would positively affect a firm's operational efficiency. The Z statistics of Sobel tests show that the mediation effect of trade credit is marginally significant (significant at the 5% level in the one-tailed test). The findings support *Hypothesis 2a*.

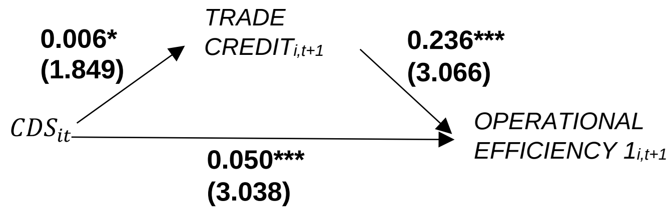
We further explore the impacts of CDS trading on firm institutional monitoring. We use the firm's institutional ownership ratio as a measure of institutional monitoring (*Institutional Ownership*). Panel B of Table 9 presents the results. The results show that the initiation of CDS trading could significantly increase institutional ownership and the institutional monitoring could significantly increase the firm's operational efficiency. The Sobel tests of the coefficient estimate of $\beta_1 \times \gamma_1$ are significant. Our findings are supporting *Hypothesis 2b*.

[10] Since trade credit is short-term operational resources, so we use the trade credit in year t+1, which is in the same period as operational efficiency, in our regression model.

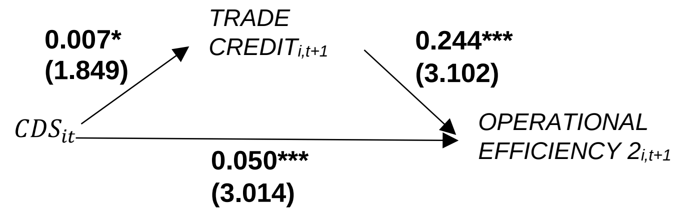
Table 9. Test of Mediating Effect

Panel A. Mediating Effect of Trade Credit

OPERATIONAL EFFICIENCY $1_{i,t+1}$



OPERATIONAL EFFICIENCY $2_{i,t+1}$

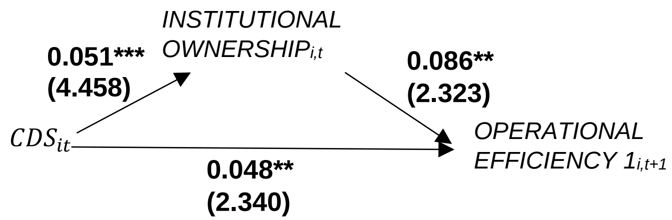


	OPERATIONAL EFFICIENCY $1_{i,t+1}$		*OPERATIONAL EFFICIENCY $2_{i,t+1}$*	
	Coef ($\beta_1 \times \gamma_1$)	Z	Coef ($\beta_1 \times \gamma_1$)	Z
Goodman	**0.0016**	**1.649***	**0.0017**	**1.653***

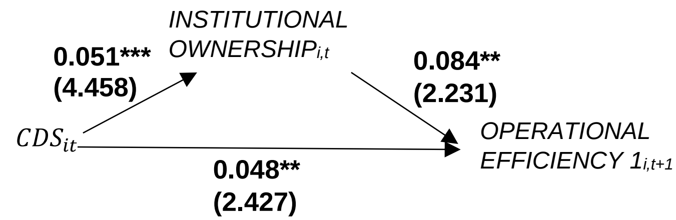
Notes. *t* statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Panel B. Mediating Effect of Institutional Ownership

OPERATIONAL EFFICIENCY $1_{i,t+1}$



OPERATIONAL EFFICIENCY $2_{i,t+1}$



	OPERATIONAL EFFICIENCY $1_{i,t+1}$		*OPERATIONAL EFFICIENCY $2_{i,t+1}$*	
	Coef ($\beta_1 \times \gamma_1$)	Z	Coef ($\beta_1 \times \gamma_1$)	Z
Goodman	**0.0043**	**2.102****	**0.0042**	**2.036****

Notes. *t* statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.5 Additional Tests

4.5.1. Relative Time Model

Our tests have shown that CDS trading on a firm's debt would increase the firm's operational efficiency by enhancing the firm's supply chain financing ability. Manifesting this effect takes time for this process. Then, related questions include how long it takes for CDS trading to take effect on the firm's operational efficiency and whether this effect lasts for a long time. To answer this question, we will conduct a dynamic-DiD test using our PSM-matched sample in this section. Table 10 shows the results. $YEAR^{-j}$ ($YEAR^{j}$) is the pre-CDS (post-CDS) year indicator that equals 1 in j^{th} year before (after) the first CDS trading year for CDS active firm *i*; otherwise, 0. From the results, we can see that it takes four years for this effect to become significant and robust, and this effect is a long-lasting effect as the positive relation between CDS trading and operational efficiency persists after four years. Besides, the insignificant coefficients of $YEAR^{-2}$, $YEAR^{-3}$, $YEAR^{-3^+}$ year indicators support the parallel trend assumption. The coefficients of $YEAR^{-1}$ are negatively significant, meaning that in our PSM-matched sample, the operational efficiency of CDS active firms is lower than control firms one year before CDS trading. The difference, however, is in opposite direction to the post-CDS difference and does not affect the interpretation of our results. In addition, the results alleviate the concern that the positive relation between CDS trading and operational efficiency is driven by chance or other time series latent factors. We also conduct the test using the CEM-matched sample, and the results are shown in the Online Appendix (Table OA9).

Table 10. Relative Time Model Based on PSM-Matched Sample (Sample year: 1994-2014)

	(1) *OPERATIONAL EFFICIENCY $1_{i,t+1}$*	(2) *OPERATIONAL EFFICIENCY $2_{i,t+1}$*	(3) *OPERATIONAL EFFICIENCY $1_{i,t+1}$*	(4) *OPERATIONAL EFFICIENCY $2_{i,t+1}$*
$YEAR^{-3^+}$	-0.014	-0.013	-0.014	-0.013
	(-0.474)	(-0.437)	(-0.385)	(-0.392)
$YEAR^{-3}$	-0.025	-0.023	-0.025	-0.023
	(-0.887)	(-0.797)	(-1.254)	(-1.009)
$YEAR^{-2}$	0.001	0.001	0.001	0.001
	(0.050)	(0.052)	(0.052)	(0.046)
$YEAR^{-1}$	-0.042**	-0.043**	-0.042**	-0.043**
	(-2.321)	(-2.346)	(-2.393)	(-2.151)
$YEAR^{1}$	-0.010	-0.009	-0.010	-0.009
	(-0.503)	(-0.465)	(-0.473)	(-0.432)
$YEAR^{2}$	-0.002	-0.001	-0.002	-0.001
	(-0.066)	(-0.046)	(-0.066)	(-0.033)
$YEAR^{3}$	0.011	0.010	0.011	0.010
	(0.406)	(0.383)	(0.337)	(0.295)
$\boldsymbol{YEAR^{4}}$	**0.057****	**0.056****	**0.057****	**0.056***
	(2.119)	**(2.078)**	**(2.360)**	**(1.737)**

$YEAR^{4+}$	**0.060****	**0.058****	**0.060****	**0.058****
	(2.245)	**(2.138)**	**(2.480)**	**(2.238)**
Controls	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Observations	3796	3796	3796	3796
R2	0.046	0.046	0.046	0.046

Notes. Robust *t* statistics in parentheses in columns (1) – (2), and bootstrap z statistics in parentheses in columns (3) – (4). All standard errors are clustered at firm level. R2 is based on fixed-effects (within) regression. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.5.2. Subgroup Tests

Another related question is how the effect of CDS trading on underlying firms' operational efficiency varies according to different firm characteristics. To answer this question in this part, we will divide the full sample into different subgroups according to different firm characteristics and re-estimate regression equation (3) to see the effect of CDS on firms' operational efficiency in different subsamples. First, given our proposition that trade credit financing and institutional monitoring are two mechanisms through which CDS affects underlying firms' operational efficiency, and our mediation tests also provide evidence to support our hypothesis, we will use trade credit level and institutional stockholders as the partition criterion.

For the trade credit level, we divide the full sample on the basis of the year-industry (2-digit SIC codes) median level. If the firm's trade credit level ($Trade\ Credit_{i,t}$) is higher (lower) than the industry (2-digit SIC codes) median level in the same year, then, the firm-year observation will be assigned to the High- (Low-) Trade Credit group. For the institutional stockholders, if firm *i* has institutional stockholders in year t, then, the observation will be assigned to the With-Institutional Stockholders group; otherwise, the observation will be assigned to the Without-Institutional Stockholders group. Table 11 (Panels A and B) displays the results, which show that the positive effect of CDS on firms' operational efficiency is significant in both trade credit groups (marginally significant in the two-tailed test and significant at the 5% level in the one-tailed test in High-Trade Credit group) and only significant for firms without institutional ownership. The results for institutional stockholders imply that CDS trading plays its role mainly in firms without institutional stockholders before CDS initiation. Then CDS trading would attract institutional investors' attention to invest in the focal firms and the increased institutional monitoring would improve firms' operational efficiency.

Next, considering that CDS is traded on firms' debt, we hypothesize that the effect of CDS on firms' operational efficiency is more significant in firms with high debt dependency. Following Rajan and Zingales (1998), we define debt dependency as the sum of debt issuance divided by the sum of capital expenditures and R&D expenses over the past three years. Then, we divide the full sample on the basis of the year-industry (2-digit SIC codes) median level. Panel C of Table 11 reports the results. They show that the positive effect of CDS trading on firms' operational efficiency is only significant in firms that are highly dependent on debt financing for investment.

Finally, we use operational uncertainty, which is measured as the standard deviation of ROA for the past five years (Cheng et al. 2021), as another firm characteristic to divide the sample. We partition the full sample into two groups according to the year-industry (2-digit SIC codes) median level of uncertainty and re-estimate the baseline regression. Panel D of Table 11 shows the results. Evidently, the positive effect of CDS trading on firms' operational efficiency is only significant in firms with stable earnings.

Table 11. Sub-Group Analysis

Panel A: Subgroup Analysis based on Trade Credit

	OPERATIONAL EFFICIENCY 1$_{i,t+1}$		*OPERATIONAL EFFICIENCY 2$_{i,t+1}$*	
	(1) Low-Trade Credit	(2) High-Trade Credit	(3) Low-Trade Credit	(4) High-Trade Credit
CDS_{it}	**0.060****	**0.040***	**0.059****	**0.042***
	(2.286)	**(1.706)**	**(2.234)**	**(1.760)**
Controls	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Observations	9196	9668	9196	9668
R2	0.008	0.010	0.008	0.010

Panel B: Subgroup Analysis based on Institutional Stockholders

	OPERATIONAL EFFICIENCY 1$_{i,t+1}$		*OPERATIONAL EFFICIENCY 2$_{i,t+1}$*	
	(1) Without-Institutional Stockholders	(2) With-Institutional Stockholders	(3) Without-Institutional Stockholders	(4) With-Institutional Stockholders
CDS_{it}	**0.097*****	0.024	**0.096****	0.025
	(2.598)	(1.200)	**(2.555)**	(1.233)
Controls	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Observations	5984	12880	5984	12880
R2	0.014	0.008	0.015	0.008

Panel C: Subgroup Analysis based on Debt Dependency

	OPERATIONAL EFFICIENCY 1$_{i,t+1}$		*OPERATIONAL EFFICIENCY 2$_{i,t+1}$*	
	(1) Low-Debt Dependency	(2) High-Debt Dependency	(3) Low-Debt Dependency	(4) High-Debt Dependency
CDS_{it}	0.035	**0.059****	0.036	**0.059****
	(1.372)	**(2.540)**	(1.393)	**(2.497)**
Controls	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Observations	9196	9668	9196	9668

R2	0.010	0.011	0.010	0.011

Panel D: Subgroup Analysis based on Firm Uncertainty

	OPERATIONAL EFFICIENCY 1$_{i,t+1}$		*OPERATIONAL EFFICIENCY 2$_{i,t+1}$*	
	(1) Low-Uncertainty	(2) High-Uncertainty	(3) Low-Uncertainty	(4) High-Uncertainty
$\boldsymbol{CDS_{it}}$	**0.061***** **(2.863)**	0.049 (1.548)	**0.060***** **(2.783)**	0.052 (1.588)
Controls	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Observations	9196	9668	9196	9668
R2	0.014	0.008	0.013	0.008

Notes: Robust t statistics in parentheses. Control variables are the same as in baseline regression. All standard errors are clustered at firm level. R2 is based on fixed-effects (within) regression. * p < 0.1, ** p < 0.05, *** p < 0.01.

4.5.3. CDS Trading and Other Financial Performance

If the CDS trading could improve firms' operational efficiency, then, the increase in operational efficiency should eventually be translated into a change in firms' financial performance. In this part, we will see the effect of CDS trading on firms' financial performance growth rate. Specifically, we first use operating income before depreciation scaled by total assets as the financial performance. Then, we use earnings before interest, taxes, depreciation, and amortization (EBITDA) scaled by total assets as another financial performance. Table 12 shows the results. From the marginally significant coefficients of CDS_{it}, we can see that firms with CDS trading on their debt have a higher financial performance growth rate than other firms, providing evidence to support that the improvement of firms' operational efficiency from CDS trading is eventually translated into a change in firms' financial performance. Our results are robust to other scaling (sales and revenues).

Table 12. CDS Trading and Other Financial Performance

	(1) *OPERATING INCOME GROWTH RATE$_{i,t+1}$*	(2) *EBITDA GROWTH RATE$_{i,t+1}$*
$\boldsymbol{CDS_{it}}$	0.107* (1.929)	0.107* (1.929)
Controls	Yes	Yes
Year Fixed Effect	Yes	Yes
Firm Fixed Effect	Yes	Yes
Observations	17458	17458
R2	0.007	0.007

Notes. Robust t statistics in parentheses. Control variables are the same as in baseline regression. All standard errors are clustered at firm level. R2 is based on fixed-effects (within) regression. * p < 0.1, ** p < 0.05, *** p < 0.01.

5. Discussion and Conclusions

In this study, we investigate the impact of CDS trading on underlying reference firms' operational efficiency. We first document that CDS trading can significantly improve the underlying reference firm's operational efficiency. Then, we further explore the channels under the positive relation between CDS trading and a firm's operational efficiency. In particular, we find that CDS presence enhances the trade credit of the underlying firm. We also postulate that CDS improves institutional monitoring and then obtains some support. Additionally, we find that the improvement effect of CDS on focal firms' operational efficiency is more significant in firms with low trade-credit levels, with no institutional investors, with high dependence on debt for investment, and with stable earnings. This paper fills an important gap in the literature about the relation between CDS inception and a firm's operational efficiency. It provides a comprehensive understanding and empirical evidence of how financial innovations affect operational efficiency through supply chain finance and stakeholder relationships. We address the concerns that the timing of the CDS introduction is endogenous by employing several causal identification strategies and establishing a robust quantitative relationship between the inception of CDS and the operational efficiency of underlying reference firms.

Our research contributes to the literature in several ways. Previous studies by various scholars have examined how internal practices, resources, and capabilities lead to superior operational efficiency. Researchers have examined how different management practices, supply chain relationships, and IT innovations contribute to the operational performance and profitability of firms. We examine a different dimension as how operational capability can be improved and channeled through external facets. We study how external financial innovations could have affected the operational efficiency of firms.

We explore how financial innovations could lead firms to a different position in the supply chain and gain efficiency and competitive advantage through such an external positional advantage. Theoretically, we help scholars understand how competitive advantage can possibly be generated as firms are positioned differently in the financial market (Johnson and Greening 1999; Parmigiani et al. 2011). We show how efficiency and competitiveness can be generated in a very different way. We contribute to the RBV of the firm by understanding how a different positional advantage can lead to a different level of supply chain advantage and efficiency (Parmigiani et al. 2011; Hitt et al. 2016). We show how positional differences lead to distinctive stakeholder pressures and advantages, enabling the firm to obtain efficiency gains. We also postulate how financial innovation through CDS can shape the governance, managerial control, and efficiency of firms (Freeman 1999; Harrison and Wicks 2013) and then obtain some weak support through our analyses. In this regard, we provide a different theoretical perspective as how external innovations lead to internal efficiency through supply chain capability, finance, and corporate control.

Our findings are important to operations managers. Practitioners, particularly those in a senior management position, need to understand that the efficiency and competitive advantage of firms do not come only internally through stronger systems and routines within the firm but potentially through external resources such as a different positioning in the financial market. From a strategic perspective, improvements in efficiency and operations do not come only from continuous process enhancements as initiated by the firms but are shaped by many external factors, including financial innovations such as CDS inception and a different positioning in the financial market. This finding is extremely important because, through a complete understanding of how operational advantage and efficiency are generated, operations and supply chain executives are equipped with better knowledge, techniques, and resources to improve operational efficiency as opportunities arise. Without such an understanding, practitioners are likely to miss many valuable opportunities to take advantage of the external prospects and possibilities as business environments continue to evolve. Thus the management must pay attention to and respond to external stimuli such as financial markets and related innovations—such resources and advantages from external could be well integrated with firms' daily operations and further establish firms' additional efficiency and competitive advantage. Our analysis also shed light on how the management could gain or enhance the newly established competitive advantage in internal governance, deal negotiation (debt dependency), supply chain management, risk management, and firms' overall financial performance.

An understanding of the positional advantage of a firm and how it enhances efficiency through RBV is also critical to supply chain professionals as they deal with various issues related to supply chain finance and capability (Craighead et al. 2009; Wuttke et al. 2019). Overall, this paper offers a supplementary or alternative view to both academics and practitioners on how efficiency and competitive advantage are generated. We present one of the first studies showing how financial innovations can affect operational efficiency and what potential channels the influences might generate.

Our findings have direct implications for the ongoing policy debate regarding CDSs. As an important financial innovation in recent decades, CDSs remain controversial. In the 2007–2009 credit crisis, CDSs were considered the facilitator of synthetic mortgage-backed securities. During the sovereign default episodes of Greece and Argentina, CDS buyers were criticized for speculating on government defaults. Consequently, CDS has drawn the attention of many financial regulators and was regulated by the Basel III bank regulations and the Dodd-Frank Act (Augustin et al. 2014). Nonetheless, CDS trading has been shown to promote risk-sharing (Saretto and Tookes 2013) and improve a firm's innovation by facilitating underlying reference firms' risk-taking behaviors (Chang et al. 2019). Our research provides robust empirical evidence of how the inception of CDS spurs operational efficiency through supply chain finance, highlighting the beneficial effect of CDS trading on improved efficiency. By reducing information asymmetry, CDS trading can effectively enhance underlying reference firms' debt capacities. Therefore, these underlying reference firms are able to obtain higher trade credit through supply chain finance and improve operational efficiency.

The financial market is under rapid changes with surging innovative financial products. Financial innovations, although apparently unrelated to internal operations of firms, indeed could change firms' relations with other stakeholders and lead to a different relational dynamism in the supply chain, potentially empowering firms to do differently and improve efficiency. An urgent need arises for OM scholars to understand how the change in relationship dynamics due to external innovations might affect operations and firm performance. In the rapidly changing business environment, innovative business practices are consistently generated in different functional areas, and one area of innovation can intentionally or unintentionally affect the other, as we demonstrate in this research.

The current research has some limitations. First, although our study demonstrates a bright side of CDS trading in its capacity to enhance operational efficiency, a caveat is that our empirical analysis focuses on the operational efficiency of underlying reference firms and does not capture all of the complex welfare effects of CDS trading. The regulation of CDS markets should be based on the trade-off between the beneficial and detrimental effects of CDS trading, and our research only highlights one such beneficial effect of CDS trading. Second, the absence of a comprehensive data source for CDS transactions prevented us from examining the impact of CDS trading volume on operational efficiency, and prevented us from investigating the effect of CDS abandonment, the opposite of CDS inception, on operational efficiency. We may conduct the relevant analysis in the future when we can get access to the detailed data, which can help us understand the effect of CDS on operational efficiency more comprehensively. Third, our current research only investigates two underlying channels through which CDS trading could affect operational efficiency. There may be other channels or CDS could affect operational efficiency directly. This could be investigated with additional theoretical analysis and detailed CDS trading data in the future, through which we can have a more comprehensive understanding of how CDS trading affects operational efficiency.

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References

Alan, Y., G. P. Gao, V. Gaur. 2014. Does inventory productivity predict future stock returns? A retailing industry perspective. *Management Science* **60**(10) 2416-2434.

Ashcraft, A. B., J. A. Santos. 2009. Has the CDS market lowered the cost of corporate debt? *Journal of Monetary Economics* **56**(4) 514–523.

Augustin, P., M. G. Subrahmanyam, D. Y. Tang, S. Q. Wang. 2014. Credit default swaps: A survey. *Foundations and Trends® in Finance* **9**(1–2) 1-196.

Bapna, S., M. J. Benner, L. Qiu. 2019. Nurturing online communities: An empirical investigation. *MIS Quarterly* **43**(2) 425-452.

Bardhan, I., V. Krishnan, S. Lin. 2013. Business value of information technology: Testing the interaction effect of IT and R&D on Tobin's Q. *Information Systems Research* **24**(4) 1147-1161.

Barth, J. R., C. Lin, Y. Ma, J. Seade, F. M. Song. 2013. Do bank regulation, supervision and monitoring enhance or impede bank efficiency?. *Journal of Banking & Finance* **37**(8) 2879-2892.

Battese, G. E., T. J. Coelli. 1988. Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. *Journal of Econometrics* **38**(3) 387-399.

Bellamy, M. A., S. Ghosh, M. Hora. 2014. The influence of supply network structure on firm innovation. *Journal of Operations Management* **32**(6) 357-373.

Berman, S. L., A. C. Wicks, S. Kotha, T. M. Jones. 1999. Does stakeholder orientation matter? The relationship between stakeholder management models and firm financial performance. *Academy of Management Journal* **42**(5) 488-506.

Blackwell, M., S. Iacus, G. King, G. Porro. 2009. cem: Coarsened exact matching in Stata. *The Stata Journal* **9**(4) 524-546.

Bolton, P., M. Oehmke. 2011. Credit default swaps and the empty creditor problem. *Review of Financial Studies* **24**(8) 2617–2655.

Burkart, M., T. Ellingsen. 2004. In-kind finance: A theory of trade credit. *American Economic Review* **94**(3) 569-590.

Carter, M. E., L. J. Lynch. 2001. An examination of executive stock option repricing. *Journal of Financial Economics* **61**(2) 207-225.

Chang, X., Y. Chen, S. Q. Wang, K. Zhang, W. Zhang. 2019. Credit default swaps and corporate innovation. *Journal of Financial Economics* **134**(2) 474-500.

Chava, S., R. Ganduri, C. Ornthanalai. 2018. Are credit ratings still relevant?. Working paper, Available at SSRN: https://ssrn.com/abstract=2023998.

Chen, Y., H. K. Cheng, Y. Liu, J. Pu, L. Qiu, N. Wang, 2022. Knowledge-sharing ties and equivalence in corporate online communities: A novel source to understand voluntary turnover. *Production and Operations Management*, Forthcoming.

Chen, T., Cheng, H. K., Jin, Y., Li, S., Qiu, L. 2021. Impact of Competition on Innovations of IT Industry: An Empirical Investigation. *Journal of Management Information Systems*, **38**(3), 647-666.

Cheng, H. K., Fan, W., Guo, P., Huang, H., Qiu, L. 2020. Can "gold medal" online sellers earn gold? The impact of reputation badges on sales. *Journal of Management Information Systems*, **37**(4), 1099-1127.

Cheng, Z., A. Rai, F. Tian, S. X. Xu. 2021. Social learning in information technology investment: the role of board interlocks. *Management Science* **67**(1) 547-576.

Chizema, A., X. Liu, J. Lu, L. Gao. 2015. Politically connected boards and top executive pay in Chinese listed firms. *Strategic Management Journal* **36**(6) 890-906.

Craighead, C. W., G. T. M. Hult, D. J. Ketchen Jr. 2009. The effects of innovation–cost strategy, knowledge, and action in the supply chain on firm performance. *Journal of Operations Management* **27**(5) 405-421.

Ding, Y., Tu, Y., Pu, J., and Qiu, L. 2021. Environmental Factors in Operations Management: The Impact of Air Quality on Product Demand. *Production and Operations Management*, **30**(9), 2910-2924.

Dutta, S., O. M. Narasimhan, S. Rajiv. 2005. Conceptualizing and measuring capabilities: Methodology and empirical application. *Strategic Management Journal* **26**(3) 277-285.

Fan, W., Zhou, Q., Qiu, L., and Kumar, S. 2022. Should Doctors Open Online Consultations? An Empirical Investigation of How It Impacts Offline Appointments. *Information Systems Research*, Forthcoming.

Fisman, R., I. Love. 2003. Trade credit, financial intermediary development, and industry growth. *The Journal of Finance* **58**(1) 353-374.

Freeman, R. E. 1999. Divergent stakeholder theory. *Academy of Management Review* **24**(2) 233-236.

Galil, K., O. M. Shapir, D. Amiram, U. Ben-Zion. 2014. The determinants of CDS spreads. *Journal of Banking & Finance* **41** 271-282.

Goh, K. Y., C. S. Heng, Z. Lin. 2013. Social media brand community and consumer behavior: Quantifying the relative impact of user-and marketer-generated content. *Information Systems Research* **24**(1) 88-107.

Harrison, J. S., A. C. Wicks. 2013. Stakeholder theory, value, and firm performance. *Business Ethics Quarterly* **23**(1) 97-124.

Hendricks, K. B., V. R. Singhal, R. Zhang. 2009. The effect of operational slack, diversification, and vertical relatedness on the stock market reaction to supply chain disruptions. *Journal of Operations Management* **27**(3) 233-246.

Hitt, M. A., K. Xu, C. M. Carnes. 2016. Resource based theory in operations management research. *Journal of Operations Management* **41** 77-94.

Iacus, S. M., G. King, G. Porro. 2012. Causal inference without balance checking: Coarsened exact matching. *Political analysis* **20**(1) 1-24.

Ivanov, I. T., J. A. Santos, T. Vo. 2016. The transformation of banking: Tying loan interest rates to borrowers' CDS spreads. *Journal of Corporate Finance* **38** 150-165.

Jacobs, B. W., R. Kraude. S. Narayanan. 2016. Operational productivity, corporate social performance, financial performance, and risk in manufacturing firms. *Production and Operations Management* **25**(12) 2065-2085.

Johnson, R. A., D. W. Greening. 1999. The effects of corporate governance and institutional ownership types on corporate social performance. *Academy of Management Journal* **42**(5) 564-576.

Jondrow, J., C. K. Lovell, I. S. Materov, P. Schmidt. 1982. On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics* **19**(2-3) 233-238.

Khurana, S., L. Qiu, S. Kumar. 2019. When a doctor knows, it shows: an empirical analysis of doctors' responses in a Q&A forum of an online healthcare portal. *Information Systems Research* **30**(3) 872-891.

Kim, G. H. 2013. Credit default swaps, strategic default and the cost of corporate debt. Working paper, Warwick Business School, University of Warwick, Coventry, UK.

Kortmann, S., C. Gelhard, C. Zimmermann, F. T. Piller. 2014. Linking strategic flexibility and operational efficiency: The mediating role of ambidextrous operational capabilities. *Journal of Operations Management* **32**(7-8) 475-490.

Kumar, S., Qiu, L. 2022. *Social Media Analytics and Practical Applications: The Change to the Competition Landscape*. CRC Press.

Kumar, N., L. Qiu, S. Kumar. 2018a. Exit, voice, and response in digital platforms: An empirical investigation of online management response strategies. *Information Systems Research* **29**(4) 849-870.

Kumar, S., V. Mookerjee, A. Shubham. 2018b. Research in operations management and information systems interface. *Production and Operations Management* **27**(11) 1893-1905.

Kumar, N., Qiu, L., Kumar, S. 2022a. A hashtag is worth a thousand words: An empirical investigation of social media strategies in trademarking hashtags. *Information Systems Research*, Forthcoming.

Kumar, S., Qiu, L., Sen, A., Sinha, A. P. 2022b. Putting Analytics into Action in Care Coordination Research: Emerging Issues and Potential Solutions. *Production and Operations Management*, Forthcoming.

Kumar, S., V. Mookerjee, T. M. Choi, X. Yue. 2020. Call for Papers: Special Issue of Production and Operations Management Journal: Disruptive technologies and operations management. *Production and Operations Management*, Call for papers.

Kusunoki, K., I. Nonaka, A. Nagata. 1998. Organizational capabilities in product development of Japanese

firms: a conceptual framework and empirical findings. *Organization Science* **9**(6) 699-718.
Lam, H. K., A. C. Yeung, T. E. Cheng. 2016. The impact of firms' social media initiatives on operational efficiency and innovativeness. *Journal of Operations Management* **47** 28-43.
Li, S., J. Shang, S. A. Slaughter. 2010. Why do software firms fail? Capabilities, competitive actions, and firm survival in the software industry from 1995 to 2007. *Information Systems Research* **21**(3) 631-654.
Li, X. 2016. Could deal promotion improve merchants' online reputations? The moderating role of prior reviews. *Journal of Management Information Systems* **33**(1) 171-201.
Lou, D. 2014. Attracting investor attention through advertising. *The Review of Financial Studies* **27**(6) 1797-1829.
MacKinnon, D. P., J. L. Krull, C. M. Lockwood. 2000. Equivalence of the mediation, confounding and suppression effect. *Prevention Science* **1**(4) 173-181.
Martin, X., S. Roychowdhury. 2015. Do financial market developments influence accounting practices? Credit default swaps and borrowers' reporting conservatism. *Journal of Accounting and Economics* **59**(1) 80–104.
Mengle, D. 2007. Credit derivatives: An overview. *Economic Review-Federal Reserve Bank of Atlanta* **92**(4) 1-24.
Morrison, A.D. 2005. Credit derivatives, disintermediation, and investment decisions. *The Journal of Business* **78**(2) 621–47.
Mukherji, P., A. Sorescu, J. C. Prabhu, R. K. Chandy. 2011. Behemoths at the gate: how incumbents take on acquisitive entrants (and why some do better than others). *Journal of Marketing* **75**(5) 53-70.
Ng, C. K., J. K. Smith, R. L. Smith. 1999. Evidence on the determinants of credit terms used in interfirm trade. *The Journal of Finance* **54**(3) 1109-1129.
Pan, Y., Qiu, L. 2022. How ride-sharing is shaping public transit system: A counterfactual estimator approach. *Production and Operations Management,* **31**(3), 906-927.
Parlour, C.A., A. Winton. 2013. Laying off credit risk: Loan sales versus credit default swaps. *Journal of Financial Economics* **107**(1) 25–45.
Parmigiani, A., R. D. Klassen, M. V. Russo. 2011. Efficiency meets accountability: Performance implications of supply chain configuration, control, and capabilities. *Journal of Operations Management* **29**(3) 212-223.
Peng, D. X., R. G. Schroeder, R. Shah. 2008. Linking routines to operations capabilities: A new perspective. *Journal of Operations Management* **26**(6) 730-748.
Petryk, M., Rivera, M., Bhattacharya, S., Qiu, L., and Kumar, S. 2022. How network embeddedness affects real-time performance feedback: An empirical investigation. *Information Systems Research*, Forthcoming.
Pirinsky, C., Q. Wang. 2006. Does corporate headquarters location matter for stock returns?. *The Journal of Finance* **61**(4) 1991-2015.
Rajan, R. G., L. Zingales. 1998. Financial dependence and growth. *American Economic Review* **88**(3) 559-586.
Saretto, A., H.E. Tookes. 2013. Corporate leverage, debt maturity, and credit supply: The role of credit default swaps. *The Review of Financial Studies* **26**(5) 1190–1247.
Shan, S.C., D.Y. Tang, A. Winton. 2015. Market versus contracting: Credit default swaps and creditor protection in loans. Working paper, Available at SSRN: https://ssrn.com/abstract=2643602.
Shim, I., H. Zhu. 2014. The impact of CDS trading on the bond market: Evidence from Asia. *Journal of Banking & Finance* **40** 460-475.
Smith, J. K. 1987. Trade credit and informational asymmetry. *The Journal of Finance* **42**(4) 863-872.
Sobel, M. E. 1982. Asymptotic confidence intervals for indirect effects in structural equation models. *Sociological Methodology* **13** 290-312.
Sobel, M. E. 1987. Direct and indirect effects in linear structural equation models. *Sociological Methods & Research* **16**(1) 155-176.
Song, L. Z., M. Song, C. A. Di Benedetto. 2011. Resources, supplier investment, product launch advantages,

and first product performance. *Journal of Operations Management* **29**(1-2) 86-104.
Subrahmanyam, M. G., D. Y. Tang, S. Q. Wang. 2014. Does the tail wag the dog?: The effect of credit default swaps on credit risk. *The Review of Financial Studies* **27**(10) 2927-2960.
Wang, H., J. Choi, J. Li. 2008. Too little or too much? Untangling the relationship between corporate philanthropy and firm financial performance. *Organization Science* **19**(1) 143-159.
Wang, H., Du, R., Shen, W., Qiu, L., Fan, W. 2022. Product reviews: A benefit, a burden, or a trifle? How seller reputation affects the role of product reviews. *MIS Quarterly* **46**(2), 1243-1272.
Wooldridge, J. M. 2010. Censored data, sample selection, and attrition. *Econometric Analysis of Cross Section and Panel Data*, 2nd ed. The MIT press, Cambridge, Massachusetts, London, England, 802-814.
Wu, Q., K. Muthuraman, S. Seshadri. 2019. Effect of financing costs and constraints on real investments: The case of inventories. *Production and Operations Management* **28**(10) 2573-2593.
Wu, S. J., S. A. Melnyk, B. B. Flynn. 2010. Operational capabilities: The secret ingredient. *Decision Sciences* **41**(4) 721-754.
Wuttke, D. A., E. D. Rosenzweig, H. S. Heese. 2019. An empirical analysis of supply chain finance adoption. *Journal of Operations Management* **65**(3) 242-261.
Yan, Z., Kuang, L., Qiu, L. 2022. Prosocial Behaviors and Economic Performance: Evidence from an Online Mental Healthcare Platform. *Production and Operations Management*, Forthcoming.
Yiu, L. D., H. K. Lam, A. C. Yeung, T. C. E. Cheng. 2020. Enhancing the financial returns of R&D investments through operations management. *Production and Operations Management* **29**(7) 1658-1678.