The Importance of Commodity Market Information to Bank Loan Contracting: Evidence from a Natural Experiment

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January 2025

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Abstract

This study investigates whether banks incorporate information embedded in commodity futures prices when assessing borrowers' creditworthiness. Using the financialization of commodity markets (FCM) since 2004 as a shock to the informativeness of commodity prices, we document that, banks charge higher loan spreads for firms with greater dependence on index commodities in their supply chain after FCM, indicating that banks account for the loss of commodity price informativeness in designing loan contracts. The rise in loan spreads is more pronounced when banks have limited access to information, firms disclose lower-quality financial reports, firms operate in opaque environments, and firms with greater default risk. Further, we show that the intensity and strictness of covenants also rise after FCM and that firm investments are constrained in the post-FCM period, with this effect being particularly acute for bank-dependent firms.

Keywords: Financialization of commodity markets; Informativeness of commodity prices; Bank loan contracting; Loan spread

JEL Classifications: M41; D82; G13; G21

1. Introduction

Since 2004, a huge number of index funds have flooded the commodity futures markets—a phenomenon known as the financialization of commodity markets (FCM). As of 2021, the trading volume of the U.S. commodity futures markets reached $40.6 trillion, equivalent to half of that of the U.S. stock market (Kang, Tang, and Wang 2023). While the massive index investing has increased the liquidity of commodity futures markets and enhanced their risk-hedging function, the resulting price bubble and economic consequences of this significant structural change have sparked a world-wide debate (OECD 2010).[1] While the dispute over its impact on commodity price volatility has not yet been resolved, a consensus exists that it reduces price informativeness (e.g., Stoll and Whaley 2010; Sockin and Xiong 2015; Brogaard, Ringgenberg, and Sovich 2019; Ferracuti 2022; Goldstein and Yang 2022). From the perspective of impeded managerial learning, prior literature focuses on the impact of FCM on firms' production decisions and organizational design (e.g., Brogaard et al. 2019; Ferracuti 2022). To date, there is little evidence of its impact on the decision process of other market participants. In this study, we extend the literature by examining how the reduced informativeness of commodity futures prices associated with FCM impacts bank loan contracting.

Exploring how bank loan contracting is affected when demand and supply

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[1] Irwin, S. and D. Sanders (2010-06-01), "The Impact of Index and Swap Funds on Commodity Futures Markets: Preliminary Results", OECD Food, Agriculture and Fisheries Papers, No. 27, OECD Publishing, Paris. http://dx.doi.org/10.1787/5kmd40wl1t5f-en.

information signals from the commodity futures markets are disrupted is important for two reasons. First, bank loans is the cornerstone of corporate financing and have a pivotal impact on economic development.[2] In 2023, commercial loans account for 47.38% of GDP in the U.S. according to GlobalData.[3] Changes in bank lending also contribute significantly to macroeconomic volatility (Broadbent, Ennis, Pike, and Sapriza 2024). If FCM disrupts the informational efficiency of commodity futures markets and thereby alters bank lending practices, its implications could cascade through the broader economy, amplifying risks for borrowers, lenders, and policymakers alike. Second, while banks are widely recognized as specialized intermediaries with advanced capabilities in information screening and processing, which benefit other capital market participants (Massa and Rehman 2008; Demiroglu and James 2010; Ma et al. 2019; Ho et al. 2024), the literature has largely ignored how information embedded in capital markets is utilized in shaping loan contracts (Chy and Kyung 2023). Existing studies on banks' information sources primarily focus on public and private information directly provided by borrowers (e.g., Bharath, Sunder, and Sunder 2008; Plumlee, Xie, Yan, and Yu 2015), neglecting the potential for banks to actively gather and integrate credit-relevant information from other markets, such as commodity futures markets. Examining this underexplored aspect can offer a deeper understanding of how banks collect and analyze information, thereby

[2] Graham, Li, and Qiu (2008) suggest that at the turn of the century, the U.S. market had $780 billion in debt issuance compared to $2 billion in equity issuance, with bank loans representing about 54 percent of debt offerings.
[3] See data published by GlobalData in May 2024 at https://www.globaldata.com/data-insights/financial-services/loans-as-a-percentage-of-gdp-in-united-states-of-america-2043548/.

shedding light on the broader mechanisms of information use in financial intermediation and risk assessment.

We poist that the demand and supply information conveyed by commodity futures prices helps banks predict the expected future cash flows of borrowers who use or produce this commodity. Banks could use such inforamtion to validate borrower-provided financial data and generate new evidence to assess borrowers' default risk. Because information from borrowers is likely to be manipulated, banks need information from alternative sources to verify borrower-provided information. Because commodity future prices contain forward-looking financial data relevant to sales and costs when borrowers produce or use the associated commodities, banks may rely on this information to assess the reliability of borrower-provided financial disclosures, especially in areas where estimates are required and are prone to managerial manipulation. Further, futures prices in commdoty futures markets allow banks to complement their information set with real-time, market-sensitive data on economic fundamentals. Accordingly, banks may gain deeper insights into a borrower's financial prospects and hence form a more accurate assessment of the borrower's credit risk. Therefore, it is possible that the reduction in the informativeness of futures prices caused by FCM raises banks' information risk (i.e., the uncertainty in assessing the borrower's creditworthiness), making banks charge a higher interest rate to compensate for the hightented risk.

However, it is also possible that FCM does not have a significant effect on bank loan contracting. Banks have privileged access to firms' private information and might establish a minimum threshold for assessing borrowers' resilience to fluctuations in demand and supply. As a result, supply and demand information from commodity futures prices may not be considered as material by banks in making lending decisions. Therefore, whether FCM impacts loan contracting remains unclear ex ante and thus warrents empirical investigation.

We begin by examining the effect of FCM on loan spreads. We use an industry's dependence on index commodities to gauge the extent to which firms in the industry are affected by FCM. An industry's dependence on index commodities is defined as the amount of index commodities as inputs or outputs divided by the sum of total inputs and outputs of this industry based on the Benchmark Input-Output tables released by the Bureau of Economic Analysis (BEA) in 2002. We employ a six-year window around 2004 (i.e., the year FCM starts) and perform a difference-in-differences (DID) analysis. Our empirical results revreal that banks factor in the reduced informativeness of futures prices and raise loan spreads for firms whose production depends heavily on index commodities after FCM. The effect of FCM is economically significant in that a one-standard-deviation increase in a firm's dependence on index commodities is associated with a 5.38 basis point (bps) rise in loan spreads in the post-FCM period, which equivalent to 4% of the sample mean loan spreads. Our results hold in a parallel trend test and various robustness checks.

Next, we conduct a series of cross-sectional analysese to verify the mechanisms through which FCM affects bank loan spreads. We document that the increase in loan spreads caused by reduced price informativeness is more pronounced for smaller banks and banks with greater geographic distance with the borrower, suggesting that the reduction in the informativeness of futures prices imposes a bigger issue for banks that lack alternative information sources. We also find that the increase in loan spreads in the post-FCM era is greater for borrowers with poorer accruals quality, less conservative financial reporting, and lower accounting comparability, and for borrowers that have more informed trading in the stock market and lower analyst and media coverage. The results indicate that information from commodity futures prices is more important for banks when the borrower has lower-quality financial reporting or operates in a less transparent information environment. The findings are consistent with our story that the reduction in the informativeness of futures prices caused by FCM raises banks' information risk, resulting in higher loan spreads.

As additional tests, we first examine the interplay between default risk and information risk, two most important types of risks in determining bank loan contracting. We find that the effect of FCM on loan spreads amplifies when borrowers have greater default risk. We further extend our analysis to non-price loan terms and find that covenants imposed on index commodity-dependent firms in bank loan contracts become more intent and stringent. Last, we document that capital investment of index commodities-dependent firms declines after FCM and the decline is more pronounced for firms with a high reliance on bank financing, suggesting that there are real consequences for the heighted borrowing costs caused by FCM.

This study makes several contributions to the literature. First, we contribute to the bank loan contracting literature by providing evidence that banks incorporate information embedded in commodity markets into the design of loan contracts. While prior studies extensively document the informational role of bank loan contracts in capital markets—showing how these contracts assist other market participants in decision-making and facilitate price discovery (Massa and Rehman 2008; Demiroglu and James 2010; Ma et al. 2019; Ho et al. 2024)—the literature is largely silent on whether banks actively gather information from market prices to inform credit risk assessments and loan contract structures (Chy and Hyung 2023). As Skinner (2011) noted, "we still do not have a very good understanding of the economic determinants of the structure of debt agreements." This study advances our understanding of how market-based signals influence loan contract design and sheds light on the mechanisms through which banks extract and apply external information in their risk assessment process.

Second, our study contributes to the literature on information risk in bank lending by identifying a novel external source of such risk—commodity futures prices. Information risk arises when banks face uncertainty in assessing borrowers' future cash flows and creditwothness due to incomplete or unreliable information (Kim, Song, and Stratopoulos 2018). While prior research has predominantly focused on borrower-specific sources of information risk, such as accounting deficiencies or weak information systems (e.g., Graham et al. 2008; Kim, Tsui, and Yi 2011; Kim, Song, and Stratopoulos 2018; Huang and Wang 2020), we explore an external market-driven factor: the reduced informativeness of commodity prices caused by FCM. Our findings demonstrate that banks price this external information risk into loan contracts, particularly for firms with high commodity dependence. By highlighting this previously underexplored risk source, we broaden the understanding of how external market dynamics shape credit risk assessments and loan contract design, offering new insights into the multifaceted nature of information risk in banking.

Finally, our study contributes to the understanding of FCM's broader economic consequences by focusing on its impact on banks—an essential yet underexplored market participant. Existing studies have shown that index trading-induced noise in commodity futures markets disrupts commodity production and demand (Sockin and Xiong 2015; Goldstein and Yang 2022), as well as firm-level decision-making (Brogaard et al. 2019; Ferracuti 2022). Building on this foundation, we provide novel evidence that FCM's distortions extend to the banking sector, leading to higher loan pricing for commodity-dependent firms and constraining their investment capacity. These findings underscore the pervasive influence of FCM across economic sectors and carry significant policy implications, particularly in highlighting the importance of regulatory initiatives aimed at restoring price informativeness in commodity markets.

2. Literature Review and Hypothesis Development

2.1 FCM and the Informativeness of Futures Prices

Traditional commodity futures markets are relatively illiquid and less functional in risk transfer, but they are unique in providing guidance to commodity production and consumption (Black 1976; Sockin and Xiong 2015). Participants in commodity futures markets consist primarily of commodity producers and users who are directly involved in commodity spot markets, such as large and wealthy agricultural firms (Foster and Viswanathan 1994). These participants typically hold private information about the fundamentals of commodity demand and supply, which they derive from independent sources. Through their trading activities, this private information is aggregated and reflected in commodity prices, making commodity prices more indicative of demand and supply dynamics (Bryant and Haigh 2004). In this regard, others can glean valuable information from the futures prices and gain insights into shifts in global economic fundamentals, thereby alleviating information frictions associated with commodity production, storage, and consumption (Cheng and Xiong 2014). Consequently, traditional commodity futures markets play a vital role in aggregating and disseminating information on commodity demand and supply, thereby supporting forward-looking assessments and fostering more informed decision-making in the real economy (Goldstein 2023).

However, since 2004, a sudden and massive inflow of commodity index investment by financial institutions has disrupted the price discovery function of commodity futures markets. As commodity futures became a favoured asset class for portfolio investors—such as pension funds and endowments—billions of dollars from index investing funds poured into these markets, raising from an estimated US$15 billion in 2003 to more than US$200 billion in 2008 (CFTC 2008). This shift, often referred to as FCM, has altered the traditional roles of commodity futures in risk-sharing and information discovery (e.g., Tang and Xiong 2012; Cheng and Xiong 2014). Because this surge in trading volumes is primarily driven by passive index investors aiming for portfolio diversification (Stoll and Whaley 2010; Irwin and Sanders 2011) rather than trading based on private information about the underlying commodities, the changing composition of market participants has significantly reduced the sensitivity of futures prices to economic fundamentals (Goldstein and Yang 2022). Prior research finds that FCM has markedly reduced the informativeness of index futures prices, severely impairing the market's ability to extract demand and supply signals (Stoll and Whaley 2010; Cheng et al. 2015; Henderson et al. 2015; Sockin and Xiong 2015; Brogaard et al. 2019).

In addition to reducing market efficiency, recent studies have found that FCM also has real effects on corporate operations and strategic decisions. For instance, Brogaard et al. (2019) document that firms that reliant on index commodities become less informed and thus make poorer investment choices after FCM, resulting in an approximate 40% decline in these firms' profits. Ferracuti (2022) finds that these firms, in an effort to establish alternative information channels, are more likely to build vertical connections with their customer and supplier industries through interlocking directors or to pursue vertical integration. Such practices indicate that firms have to bear higher operational costs to counteract the informational disruptions introduced by FCM.

2.2 Information Risk in Bank Lending

The traditional banking literature suggests that default risk is the major lending risk faced by banks and is one of the primary determinants of loan pricing. Greater default risk typically results in higher interest rates. However, as research has progressed, information risk—arising from uncertainty about the quality, reliability, or availability of information—has been recognized as another key determinant of bank loan contracting. Limited or unreliable information increases uncertainty in credit assessments, compelling banks to impose higher interest rates or stricter loan covenants to compensate for the elevated risk.

According to Stiglitz and Weiss (1981), information asymmetry—where lenders cannot fully observe the true creditworthiness of borrowers—leads to credit rationing and inefficient market outcomes. In this context, banks face the challenge of assessing a borrower's risk, especially when information is incomplete or of questionable quality. Diamond (1984) expands on the theory by arguing that banks, as delegated monitors, are able to mitigate this information gap through careful evaluation and monitoring, yet they must still contend with the inherent risks posed by inaccurate or incomplete information. Thus, improved information disclosure can reduce information asymmetry, allowing banks to more accurately assess borrower risk and, as a result, to offer lower interest rates and better loan terms to more transparent borrowers.

Empirical studies validate and extend these theoretical insights by demonstrating an impact of information risk on loan pricing and structure. Research consistently shows that firms with high-quality financial reporting and transparent disclosures benefit from lower borrowing costs, as lenders perceive reduced information risk. For example, studies by Sengupta (1998) and Blackwell et al. (1998) confirm that lower information asymmetry, facilitated through higher-quality financial disclosures or reputable auditors, correlates with lower interest rates. In addition to formal financial reporting, banks draw on various relational and historical sources to reduce information risk. These sources include borrowers' credit histories (Diamond 1991), bank account activities (Petersen and Rajan 1994), and information gathered through interpersonal or cultural linkages (Engelberg et al. 2012; Fismanet et al. 2017). Additionally, banks also incorporate external and market-based indicators into their assessments, including sector-specific and regional economic conditions (Berger and Udell 2006), information on networks and strategic partnerships (Kadapakkam and Oliveira 2021; Guan et al. 2023), and even trading signals from secondary bond markets (Chy and Kyung 2023).

2.3 Hypothesis Development

Prior studies suggests that commodity futures prices synthesize private information from a wide range of sources, making them sensitive to shifts in economic fundamentals. This sensitivity supports forward-looking evaluations and enhances decision-making in the real economy (Bryant and Haigh 2004; Goldstein 2023). Drawing on this, we argue that information embedded in commodity futures prices can facilitate bank loan contracting through two roles: by verifying borrower-provided information and by offering decision-useful insights.

While banks have direct access to borrowers' private information by requesting their most recent financial reports and projections, borrowers often have incentives to manipulate this financial information to secure more favorable loan terms or avoid covenant violations (e.g. Bartov 1993; Dechow et al. 1996; DeFond and Jiambalvo 1994; Franzet et al. 2014; Jiang 2008; Sweeney 1994). Recognizing this, banks are cautious about the realiability of borrower-provided information. In this case, the information provided by an independent third party would assist banks in verifying their initial assessments. Commodity futures markets, in particular, can play such a role. Commodity future prices contain forward-looking financial data relevant to sales and costs when borrowers produce or use the associated commodities. This information helps banks assess the reliability of borrower-provided financial disclosures, especially in areas where estimates are required and are prone to managerial manipulation. For instance, futures prices can assist banks in verifying whether firms have adequately accounted for inventory write-downs or asset impairments, as well as in assessing the reasonableness of cost projections and gross margin estimates.

Better still, these prices are objective as it is difficult for the borrowers to manipulate them. To this end, banks are able to draw on commodity futures markets to gauge the quality of borrower-provided information, ascertaining which portions of financial disclosures are credible.

Further, futures market serves as an accessible and efficient information channel, allowing banks to complement their internal assessments with real-time, market-sensitive data on economic fundamentals. Prior research has shown that banks incorporate information from various sources to support their assessments of borrower creditworthiness (Berger and Udell 2006; Kadapakkam and Oliveira 2021; Guan et al. 2023; Chy and Kyung 2023). By leveraging the information embedded in futures prices, banks can gain deeper insights into a borrower's financial prospects and ultimately form a more accurate assessment of credit risk. While banks could alternatively gather relevant data from other sources to forecast the borrower's future sales and costs, doing so may involve significant information-gathering and processing costs and expose them to the risk of incomplete information. Therefore, the futures market—by consolidating a uniquely comprehensive range of private information through active trading—serves as an invaluable, low-cost channel, enabling banks to efficiently monitor real-time shifts in borrower creditworthiness.

Based on the above discussions, the reduction in the informativeness of futures prices caused by FCM is expected to increase the information risk for banks when assessing the creditworthiness of borrowers whose production is heavily depends on index commodities. This decline in informativeness makes it more challenging for banks to verify borrower-provided information and raises the costs of gathering and processing additional data. Consequently, banks are likely to demand higher interest rates to compensate for this elevated information risk. Based on this reasoning, we propose the following hypothesis:

> *H1: Banks charge higher loan spreads for borrowers who use or produce index commodities after a reduction in commodity futures prices.*

However, this hypothesis is not without tension. Firms that borrow from banks are typically required to disclose certain information and keep it regularly updated. If banks perceive an increased risk of default, they can request additional disclosures and renegotiate loan terms. This privileged access to firms' private information (Bharath et al. 2008; Plumlee et al. 2015; Cheng 2017) may reduce banks' reliance on information from commodity prices. Moreover, banks tend to adopt conservative strategies (Aghamolla and Li 2018; Khan and Lo 2019), suggesting that they might establish a minimum threshold for assessing borrowers' resilience to fluctuations in demand and supply. With this buffer against demand and supply risks, banks' primary concern is whether borrowers maintain sufficient net assets for ongoing loan repayments. As a result, it remains ex-ante unclear whether banks raise loan spreads for borrowers that use index commodities after the informativeness of commodity futures prices is reduced.

3. Research Design and Sample Selection

3.1 Identification Strategy

We exploit the financialization of commodity market as our research setting to capture the exogenous reduction in the informativeness of futures price, which allows us to adopt a generalized difference-in-differences research design (e.g. Brogaard et al. 2019; Ferracuti 2022). Spcifically, we perform the following model to examine our research question:

$$Log(SPREAD_{ijt}) = \beta_0 + \beta_1 \times INDEX\_DEP_i \times POST_t + \gamma' X_{it} + \eta' L_{jt} + f_i + f_t + f_l + f_p + \varepsilon_{ijt} \quad (1)$$

where the subscripts i, j, t, l, and p represent firm, loan facility, year, loan type, and loan purpose, respectively.

The dependent variable, *Log*(*SPREAD*), is the natural logarithm of the all-in-drawn spread for the loan facility. Consistent with Graham et al. (2008), we employ the logged transformation of loan spread to mitigate the potential skewness in its distributions. The independent variable, *INDEX_DEP*, reflects the firm's dependence on index commodities. We follow prior studies and define index commodities as those included in either the S&P Goldman Sachs Commodity Index (GSCI) or the Dow Jones UBS Commodity Index (UBS).[4] Following Ferracuti (2022), we construct an industry-

[4] The index commodities can be classified as agriculture, energy, or metals. Agricultural index commodities include corn, soybeans, wheat (Chicago and Kansas), soybean oil, coffee, cotton, sugar, cocoa, cattle (feeder and live), and lean hogs. Energy index commodities include crude oil (West Texas Intermediate (WTI) and Brent), heating oil, gasoline, and natural gas. Metals index commodities include gold, silver, copper, aluminum, nickel, and zinc.

level measure to quantify each industry's exposure to index commodities using the Benchmark Input-Output tables published by the BEA in 2002.[5] Specifically, *INDEX_DEP* is calculated as the percentage of the total amount of index commodities produced or used by the firm's industry to the total amount of the industry's inputs and outputs calculated using the Benchmark Input-Output table. The variable *POST* is an indicator variable set to one for years between 2005-2007 and zero for 2001-2003.

X is a set of control variables selected following prior literature. It includes firm-level characteristics as follows: *SIZE* is the natural logarithm of total assets; *TANGI* is the value of net property, plant, and equipment divided by total assets; *CASH* is cash divided by total assets; *WORKCAP* is working capital divided by total assets; *LEV* is the book value of long-term debt plus debt in current liabilities divided by book assets; *SALESGTH* is the growth rate of the firm's annual sales; *CAPX* is capital expenditure divided by total assets; *R&D* is R&D expenses divided by total assets; *ROA* is operating income before depreciation divided by beginning-of-period assets; *OPCF* is operating cash flow divided by divided by total assets; and *ZSCORE* is the modified Altman's (1968) Z-score, reflecting the financial health of the firm.

Considering that the level of loan spread could also be affected by other loan terms (Bharath et al. 2008; Graham et al. 2008; Kim et al. 2011; Hope et al. 2023), *L* incorporates important loan characteristics identified in prior studies (e.g. Campello

[5] As there are no other commodity and industry identifiers available in the Benchmark Input-Output tables, we manually match commodities with the GSCI or UBS using commodity names, and industries with Compustat firms using industry names.

and Gao 2017; Hasan et al. 2017), including: *LOANAMOU*, the natural logarithm of the loan facility amount; *LOANMATU*, the natural logarithm of the number of months to maturity of the loan facility; *LOANCOLL*, an indicator variable set to one if the loan is secured by collateral and zero otherwise; and *LOANSYND*, an indicator variable set to one if the loan is a syndicated loan and zero otherwise.

Finally, we include firm fixed effects f_i to account for the influence of firm-level time-invariant characteristics and year fixed effects f_t to control for the impact of macroeconomic factors on loan spread determination. Additionally, we incorporate loan type fixed effect f_l and loan purpose fixed effect f_p into our regressions to adjust for the unobserved influence of loan type and purpose. Throughout our analyses, the *t*-statistics are calculated based on standard errors corrected for heteroskedasticity and clustered at the firm level.

The coefficient of interest is β_1, which captures the change in loan spread for firms heavily reliant on index commodities in their business activities before and after FCM, relative to the change for firms who do not dependent on index commodities. If FCM leads banks to increase loan spreads to compensate for the reduced informativeness of futures prices, we would expect to observe β_1 to be significantly positive.

3.2 Sample

Our initial sample comprises all U.S. firms that have bank loan data in the Loan Pricing Corporation (LPC) DealScan database for years between 2001 to 2003 and 2005 to 2007. Following Ferracuti (2022), we restrict our sample to three years before (i.e., 2001-2003) and three years after (i.e., 2005-2007) the onset of FCM in 2004. This timeframe provides us with sufficient time to capture banks' responses to the information loss and minimize the impact of confounding events (e.g., the 2008 Global Financial Crisis). DealScan loan data are compiled for each transaction or deal, which may involve either a single facility or a package of several facilities with different price and non-price terms (Kim et al. 2011). In our analyses, we consider the loan facility as the unit of observation, as loan characteristics and spreads may differ across the facilities that a firm obtains within a given year (Hasan et al. 2017).

We obtain corporate financial information from Compustat, stock return data from the Center for Research in Security Prices (CRSP), analyst coverage data from the Institutional Broker Estimates System (I/B/E/S), and media news data from Capital IQ's Key Development database. Following prior studies (e.g., Hope et al. 2023), we exclude financial firms (with SIC codes between 6000 and 6999) and utilities firms (with SIC codes between 4900 and 4999) from our sample. After eliminating observations with missing values in any variables in our baseline model, the final sample consists of 11,864 loan facilities from 2,499 unique firms. To mitigate the influence of outliers, we winsorize all continuous variables at the top and bottom 1% levels.

3.3 Descriptive Statistics

Table 1 presents the descriptive statistics of the variables. The logged loan spread variable exhibits a mean (median) value of 5.022 (5.298), which corresponds to 151.71

(199.93) bps. The average index commodities dependence is 0.032. The sample firm has an average size measured by total assets of US$1510.20 million, an average leverage ratio of 0.354 and positive profitability with *ROA* of 0.152. The average loan in our sample has an amount of US$122.55 million, with a maturity period of 40.25 months.

[Insert Table 1 about here]

4. FCM and Bank Loan Spread

4.1 Baseline Results

Table 2 presents the baseline results of our regression estimations. In Column (1), we estimate Equation (1) on our sample and observe a positive and statistically significant coefficient on the interaction term *INDEX_DEP×POST* (0.329, *t*-stat = 2.67). This result suggests that a reduction in the informativeness of commodity futures prices leads banks to raise loan spread for firms that produce or use index commodities to compensate for hightened information risk. The effect is also economically significant. After FCM, a one-standard-deviation higher index commodity dependence (0.106) is associated with an increase in in loan spread by 5.38 bps, which represents a increase of 3.55% relative to the sample mean spread.[6] Given the average loan size of US$122.55 million in our sample, this increase in the loan spread translates to an annual incremental interest cost of US$65,932 per loan.

[6] This is computed as the difference between the sample mean load spread and the new spread that results: $exp(5.022+0.106\times0.329)$ - $exp(5.022)$ = 5.38 bps. Given the sample mean spread is 151.71 bps, this constitute an increase of 5.38/151.71 = 3.55% relative to the mean.

A critical premise in our DiD design is the parallel trend assumption, meaning that the time trend of loan spread should remain consistent across firms with varying levels of index commodity dependence if FCM does not occur. To verify whether this assumption holds in our setting, we undertake a dynamic analysis by introducing an indicator variable for each year during our sample period (e.g., *PRE*3 for year 2001, *PRE*2 for year 2002, *PRE*1 for year 2003, *POST*1 for year 2005, etc.), and re-estimate Equation (1) by replacing *POST* with these indicator variables. The estimated results are presented in Column (2) of Table 2.[7]

In Column (2), the interaction terms between the years before the FCM event (*PRE*2 and *PRE*1) and *INDEX_DEP* are both insignificant. This indicates that before FCM, there is no significant difference in the time trend of loan spread across companies with varying levels of index commodity dependence, thereby providing supporting evidence for our parallel trend assumption. Shifting gears, we observe that the interaction terms between the three years after the FCM event (*POST*1, *POST*2, and *POST*3) and *INDEX_DEP* all have significantly positive coefficients, suggesting that the effect starts to emerge after FCM. Considering the exogeneity of the FCM event, the dynamic analysis reenforces our argument that the effect of FCM on loand spread is likely causal.

[Insert Table 2 about here]

[7] Year 2000 is treated as the benchmark year in the dynamic analysis, and thus *INDEX_DEP*×*PRE3* is omitted in our estimation.

4.2 Robustness Tests

Our previous analyses provide evidence that the reduction in the informativeness of index commodity prices lead banks to raise loan spreads for firms whose production activities are highly reliant on index commodities. In this subsection, we conduct a battery of robustness tests to verify whether our results are robust to alternative sample periods, potential measurement errors, omitted variable bias, and other concerns. The results are presented in Table 3.

4.2.1 Alternative Sample Periods

In our baseline regressions, we confine our sample to a six-year period centered on 2004. While this choice allows us to minimize the influence of confounding events (e.g., the 2008 Global Financial Crisis), it remains arbitrary. To address concerns about this arbitrary choice, we follow Ferracuti (2022) and use four- and eight-year sample periods centered on 2004 as alternatives. The estimation results are presented in Panel A of Table 3. In both columns, the coefficients of *INDEX_DEP×POST* remain positive and statistically significant, suggesting that our baseline results are not driven by the choice of a particular sample period.

4.2.2 Alternative Measures

To address potential skewness in the distribution of loan spreads, our baseline regression uses log transformation of loan spread (Graham et al. 2008). In this subsection, we initially follow Kim et al. (2011) by employing raw loan spread as the dependent variable. Then, we introduce a ranked variable of loan spread as an alternative method to address the potential skewness issue. To elaborate, we categorize loans into 10 groups each year by loan spread and assign values ranging from 1 to 10 to these groups. We use the ranked variable as the dependent variable and re-estimate Equation (1) on our sample.

Further, in the baseline analysis we adopt an industry-level index commodities exposure measure. While this measure precisely captures the index commodity dependence for an industry, it may deviate from individual firms' exposure to commodity prices. To address this concern, we follow Brogaard et al. (2019) and construct a firm-level index commodity dependence measure based on the information disclosed in their annual reports. Specifically, we count the number of times each index commodity is mentioned in a firm's 10K annual report and create an indicator variable. This variable is assigned a value of one if a firm's average count of index commodity names in their 10-K reports from 2001 to 2003 ranks in the top decile among our sample firms. Then, we re-estimate Equation (1) using this firm-level index commodity measure as the independent variable. The results using these alternative measures are presented in Panel B of Table 3, which show that our findings remain consistent across these tests.

4.2.3 Placebo Tests

One potential concern regarding the validity of our identification strategy revolves around the possibility of treated firms being uniquely exposed to unobservable, time-varying commodity risk. To address this concern, we conduct a placebo test comparing firms significantly exposed to non-index commodities to those that are not. Here, non-index commodities refer to commodities that are not included in either the GSCI or the UBS Index. This placebo test is conducted on the premise that, while firms with significant exposure to both index and non-index commodities face similar commodity risk, only those exposed to index commodities experience a reduction in the information conveyed by futures prices in the post-FCM period, since FCM is the results of index investments (Tang and Xiong 2012). Consequently, firms with higher exposure to non-index commodities should not experience an increase in borrowing costs following FCM.

To test this prediction, we define a new variable, *NONINDEX_DEP*, using the same method to that of *INDEX_DEP*, but focusing on each industry's exposure to non-index commodities. We then re-estimate Equation (1) using this variable and report the results in Panel C of Table 3. We find that the coefficient loads on *NONINDEX_DEP*×*POST* is insignificant and close to zero, suggesting that exposure to commodity risk is unlikely to be a driving factor behind our main results.

[Insert Table 3 about here]

Next, we perform a placebo test by randomly assigning the index commodity dependence values to our sample firms, resulting in a pseudo-*INDEX_DEP* variable. We then re-estimate Equation (1) by replacing *INDEX_DEP* with pseudo-*INDEX_DEP*. We repeat the process 1,000 times and generate 1,000 coefficeints of pseudo-*INDEX_DEP*×*POST*. We plot the distribution of the coefficeints in Figure 1. The figure shows that the distribution is centered at zero and the actual coefficient in Column (1) of Table 2 (0.329) lies in the extreme of the distribution.[8] The results suggest that our findings in the baseline analysis is unlikely to be obtained by chance.

[Insert Figure 1 about here]

5. Mechanism Tests

In this section, we perform a series of cross-sectional tests to verify the channel through which FCM affects loan spread. Specifically, if the reduction in the informativeness of the futures market indeed raises firms' borrowing costs by increasing banks' information risk in assessing borrowers' creditworthness, we anticipate this effect to be more pronounced when banks have limited information sources, firms with poorer financial reporting quality, and firms that operate in less transparent environments.

5.1 The Impact of Bank's Information Sources

Commodity futures prices contain a wealth of demand and supply information about relevant commodities (Black 1976; Sockin and Xiong 2015), making them valuable for forecasting the performance of firms heavily dependent on these commodities. Thus, FCM may have deprived banks of an important information channel. However, this impact is likely to vary among different banks. For banks with rich information channels, the reduction in the informativeness of futures prices may not pose a significant issue, as they can easily acquire information from other sources

[8] Among the 1,000 placebo coefficients, only 5 of them exceed 0.329. Furthermore, none of the placebo coefficients has a *t*-statistics exceeding that of the actual coefficeint.

as compensation. In fact, the loss of information from the commodity futures market may even alleviate information overload for these banks. Conversely, for banks with limited information channels, the reduction in the informativeness of futures prices may result in the loss of a crucial information source. This necessitates an increase in loan spread to compensate for the heightened information risk.

To test this prediction, we use two proxies to reflect the richness of banks' information channels. The first proxy is bank size (*BANKSIZE*), measured as the bank's total assets. Large banks typically maintain a more diversified client portfolio (Demsetz and Strahan 1997). This may propel them into an advantageous position to comprehensively gather demand and supply information regarding a particular client by integrating various sources of information. As a result, they are better equipped to offset the loss of informativeness in future prices following FCM. The second proxy is the geographical proximity between the bank and its client firm (*GEOPROX*). Proximity facilitates frequent interactions between banks and clients, allowing banks to gather timely local information, thus enhancing their knowledge base (Cotugno et al. 2013). Based on these two proxies, we divide the sample into two subsamples and estimate our baseline model separately on each of them. The results are reported in Table 4.

In Columns (1) and (2), the sample firms are splited by bank size, with Column (1) reporting the results for large banks and Column (2) for small banks. A bank is considered a large bank if its total assets exceed annual median in our sample. If a loan facility is extended by a syndicate, we categorize it as originating from a large bank if at least one of its lead banks is large.[9] This is because lead banks are primarily responsible for analyzing the borrower's credit risk and provide subsequent supervision (Sufi 2007; Bharath et al. 2008). The results show that the coefficient of *INDEX_DEP×POST* is positively significant in Column (2) when the facility is provided by small banks, while not significant in Column (1). The difference in the coefficients of *INDEX_DEP* between the two subsamples is significant as well.

Columns (3) and (4) presents the results using geographic proximity as the proxy. We classify the geographic proximity between the borrower and lender as high (low) if they are in the same (different) MSA. Again, when a loan facility is provided by a syndicate, we consider the location of its lead bank. The results demonstrate that the coefficient of *INDEX_DEP×POST* is positive and significant in Column (4) when the geographic proximity between the borrower and lend is low, while not significant in Column (3) where the geographic proximity is high. The coefficient difference between the two subsamples is also statistically significant. Overall, the results suggest that small banks and banks that are distant to thei clients are affected more by the loss of informativeness in the future markets caused by FCM, consistent with our argument that banks' information sources play a role.

[Insert Table 4 about here]

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[9] Following Bharath et al. (2009), we identify a lender as lead lender if the "LeadArrangerCredit" field indicates "Yes" or if the "LenderRole" field indicates one of the following: administrative agent, agent, arranger, lead arranger, lead bank. For some loans are extended by a syndicate with multiple lead lenders, we classify it as originating from a large bank as long as one of the lead banks is large.

5.2 The Impact of Borrower's Financial Reporting Quality

Financial statements are crucial information sources for banks to assess client performance and credit risks. If the effect of FCM on loan spread indeed operates by altering banks' information acquisition and processing costs, the impact should vary among firms with different financial reporting quality. In this subsection, we examine the influence of three characteristics of information quality on the association between FCM and loan spreads: accounting quality, conservatism, and comparability. The results are reported in Table 5.

To begin with, we examine the influence of the borrower's accrual quality. Accounting information serve as a succinct overview of a firm's economic activities, and high-quality accounting information are of significant importance for users to understand a firm's operational activities and to assess the amount, timing, and uncertainty of its future net cash flow. Therefore, we anticipate that the reduction in the informativeness of future markets has a more pronounced impact for firms with lower accounting quality. To test this prediction, we use the absolute value of abnormal accruals derived from the modified Jones model (Dechow and Sloan 1995) to measure a borrower firm's accounting quality (*ACCQUALITY*), and split our sample into two groups based on the annual median of this measure. Column (1) and (2) show that the coefficient of *INDEX_DEP×POST* is only significant for firms with low accounting quality and the difference between these two coefficients is statistically significant.

Second, we investigate the impact of the borrower's accounting conservatism. Conservatism imposes a higher verification standard for good news than bad news, leading firms to recognize unrealized losses more promptly than unrealized gains (Basu 1997). Consequently, conservatism can hasten loan covenant violations, heighten the likelihood of transferring control rights to lenders (Zhang 2008; Nikolaev 2010; Li 2013), and diminish managers' incentives to manipulate earnings (Chen et al. 2007; Gao 2013; Ewert and Wagenhofer 2021) and take risks (Kravet 2014). From this perspective, we predict that the impact of reduction in the informativeness of future markets would be mitigated in firms with higher level of conservatism, as lenders can access more timely information concerning downside risks to facilitate prompt actions. We employ Basu (1997) model to gauge a firm's conservatism (*CONSERVATISM*) by measuring the asymmetric timeliness of earnings in reflecting news about expected future cash flows. Subsequently, we partition our sample into two subsamples based on the annual median of this measure and re-estimate our baseline model on these subsamples. The results presented in Columns (3) and (4) show that the coefficient of *INDEX_DEP×POST* is only positively significant for firms with low accounting conservatism and the difference between the coefficeints is significant.

Last, we consider the influence of accounting comparability. Prior studies document that firms' financial statement comparability lowers information acquisition and processing costs, and thus enhances the quality of information available to information users (De Franco et al. 2011; Kim et al. 2013; Kim et al. 2016).

If the reduction in informativeness of the future markets impedes banks' from extracting useful information to assess borrower performance, this effect should be stronger when the borrower's financial statements are less comparable, as the information processing costs for these firms are higher, and relevant information risks are greater. To measure a firm's accounting comparability (*COMPARABILITY*), we adopt the approach developed by De Franco et al. (2011) and compute a comparability score between two firms as the difference between their accounting systems in mapping economic events (as proxied by stock returns) into financial statements (as proxied by accounting earnings). To measure a firm's comparability, we first calculate the comparability score of the firm against all other peer firms within the same industry in a given year, then select the top 10 comparability scores and calculate their average, serving as the firm's comparability measure. Finally, we segment our sample into high-comparability and low-comparability firms and preform our baseline model on each subsample. The results are reported in Columns (5) and (6). Again, the coefficient of *INDEX_DEP×POST* is positively significant for firms with low accounting comparability, while not significant for those with high accounting comparability. The difference between the two coefficeints is significant as well. Collectively, We find evidence that the impact of FCM on loan spread is stronger in firms with lower accounting quality, less accounting conservatism, and less comparable financial statements, consistent with our expectation.

[Insert Table 5 about here]

5.3 The Impact of Borrower's Information Environment

Commodity futures markets attract a multitude of sophisticated investors who gather private information from various sources and base their decisions on these information (Bushee and Goodman 2007; Breugem and Buss 2019). Therefore, the trading behavior of these investors and fluctuations in futures prices can offer banks valuable information into assessing the performance of firms heavily reliant on the underlying commodities. Further, besides the futures market, banks may also obtain information relevant to clients' creditworthness from other sources. Thus, if FCM indeed affects loan spread by elevating the information risk for banks, this effect should be more pronounced for firms operating in poorer information environments. In this section, we examine the influence of a firm's information environment on the association between FCM and loan spread. We report the results in Table 6.

The first proxy we employ to measure a firm's information environment is the information asymmetry among investors, which is defined in line with Easley and O'Hara (2004) as the fraction of private information within a firm's overall information sets. According to Easley and O'Hara (2004), a higher level of information asymmetry increases a firm's cost of capital since uninformed investors cannot perfectly infer such private information from prices (Duarte et al. 2008; Mohanram and Rajgopal 2009). Therefore, in situations where information asymmetry is high, banks may find it challenging to fully grasp private information relevant to a firm's future operational performance. In such scenarios, the impact of the reduction in informativeness of futures prices would be amplified, as futures prices can be seen as aggregating all private information related to the firm's future demand and supply. To measure information asymmetry, we follow prior studies in the microstructure literature and use a measure to quantify the probability of informed trading (*INFTRADE*) (Duarte et al. 2008). Specifically, we adopt the Generalized Probability of Informed Trading (GPIN) model developed by Duarte et al. (2020). We first obtain the daily GPIN data of U.S. public firms from Professor Jefferson Duarte's website.[10] Then, we use the median value over the year to divide our sample into two groups, i.e., high-informed-trading firms and low-informed-trading firms. We re-estimate our baseline model on the two groups of firms separately. The results in Columns (1) and (2) show that the coefficient of *INDEX_DEP×POST* is significanly larger for firms with high GPIN than those with low GPIN.

Second, we consider analyst coverage as a proxy for a firm's information environment. As important information intermediaries, analysts integrate and interpret industry and firm-specific information from various sources and issue forecasts to help investors' portfolio decisions. The significant attention from a large number of analysts can enhance the dissemination of a firm's information, thus refining its information environment. Specifically, Coyne and Stice (2018) document that banks learn private information from analysts when assessing client's default risk. Therefore, under the influence of FCM, firms with lower analysts coverage will

[10] https://www.jefferson-duarte.com/home.

experience greater impact, as the costs associated with information collection and processing are further increased for these firms. To investigate this, we define analyst coverage (*ANALYST*) as the number of analysts cover the firm during the year and divide our sample firms into two groups: those with high analyst coverage and those with low analyst coverage. We then re-estimate our baseline model separately for each group. The results, presented in Column (3) and (4), show that the coefficient of *INDEX_DEP×POST* is positive and significant for firms with low analyst coverage and insignificant for those with high analyst coverage. The former coefficient is significant larger thatn the latter.

Our third proxy for information environment is media coverage. Similar to analysts, media plays a pivotal role in generating and disseminating information in the capital markets, thereby reducing information frictions between firms and information users and ultimately enhancing a firm's information environment (Fang and Press 2009; Bushee et al. 2010; Liu et al. 2014; Gao et al. 2020). We expect that the influence of FCM on loan spread is stronger for firms with lower media coverage. This is because banks face greater challenges in obtaining information from alternative sources to compensate for the information losses resulting from FCM. To measure media coverage (*MEDIA*), we count the annual amount of news items in the Key Development database for each firm in a given year. We then split our sample into two groups according to annual median of media coverage and re-estimate our baseline model on these subsamples. The results reported in Columns (5) and (6) show that the coefficient of *INDEX_DEP×POST* is significantly larger for the subsample with low media coverage than the subsample with high media coverage. Overall, we find that the influence of FCM on loan spread is more pronounced in firms with high informed trading, low analyst coverage, and low media coverage, suggesting that a poor information environment amplifies the impact of FCM on loand spread.

[Insert Table 6 about here]

6. Further Analyses

6.1 The Interaction between Default Risk and Information Risk

Our main analysis provides evidence that FCM increases firms' borrowing costs due to heightened information risks faced by banks. In this section, we explore the interaction between default risk and information risk, and we investigate whether the association between FCM and bank loan spreads varies among firms with different levels of default risk. Firms with higher default risk inherently pose greater challenges for lenders in assessing creditworthiness. In such cases, banks may rely more heavily on accurate and timely information to evaluate a firm's financial health, as access to precise data reduces uncertainty and facilitates better risk assessment (Merton 1974; Petersen and Rajan 1994). When FCM reduces the informativeness of commodity prices and deprives banks of a critical information source, this heightened information risk necessitates a higher risk premium, especially for borrowers with higher default risk. Accordingly, we predict that the association between FCM and bank loan spreads is more pronounced among firms with greater default risk.

To test this prediction, we employ three proxies for firm default risk. The first one is Altman's Z-score (*ZSCORE*), a higher value of which indicates lower default risk. The second proxy is the distance-to-default measure (*DISTDEFAULT*), calculated using the model proposed by Bharath and Shumway (2008). A higher value of the meaure indicates a lower likelihood of default. The third proxy is we employed is cash flow volatility (*CFVOLATILITY*). A highly uncertain operating environment would increase a firm's likelihood to default and thus we anticipate that the influence of FCM on loan spread should be stronger in such scenarios. We calulate *CFVOLATILITY* as the standard deviation of the ratio of operating cash flow over total assets during the past five years. We partition our sample into two subsamples by each of the three proxies and re-estimate our baseline regression for the subsamples.

The results are reported in Table 7. Columns (1) and (2) present the results for Altmam's Z-score, which show that the coefficient of *INDEX_DEP×POST* is significantly larger for the subsample with lower Z-score than the subsample with higher Z-score. In Columns (3) and (4), we present the results for distance-to-default. The coefficient of *INDEX_DEP×POST* is for the subsample with lower distance-to-default and the difference between the coefficient is significant. The results for cash flow volatility are reported in Columns (5) and (6), which show that the coefficient of *INDEX_DEP×POST* is significantly larger for the subsample with higher cash flow volatility than that with lower cash flow volatility. Collectively, the results in this section suggest that higher level of default risk magnifies the effect of FCM on loan spread, consistent with our expecation.

[Insert Table 7 about here]

6.2 FCM and Loan Covenants

In addition to examining loan spread, we also investigate the influence of FCM on the non-pricing terms of loan contracts. Non-pricing terms, such as covenants, are employed to restrict the financial and investment activities of the borrowing firms and to strengthen oversight by the lending banks. If the reduction in the informativeness of index futures prices heightens information risks faced by banks, we anticipate that lending banks will impose more and/or stricter covenants in loans contracts for firms heavily reliant on such commodities. However, Jiang et al. (2010) propose that lenders might opt to substitute between pricing and non-pricing terms within loan contracts. If this scenario holds true, we may not observe a positive relation between FCM and loan covenants, as all influences of FCM have already been factored into loan spreads.

To empirically examine the relation between FCM and loan covenants, we adopt the following variables to measure the intensity and the strictness of loan covenants: *CONVEN_TOTAL* represents the total number of covenants included in a loan contract; *CONVEN_GEN* and *CONVEN_FIN* denote the total number of general and financial covenants, respectively; *CONVEN_STRICT* is defined as the probability of covenant violation following Murfin (2012). The regression results using these covenant variables are presented in Table 8. In Column (1), where *CONVEN_TOTAL* serves as the dependent variable, we observe a positive and significant coefficient of

INDEX_DEP×POST, suggesting that banks impose more loan covenants after FCM.

In Columns (2) and (3) where total covenants are categorized into general and financial ones, we find that the rise in the number of loan covenants is primarily attributed to general covenants. Unlike financial covenants which primarily focus on figures in financial statements, general covenants impose direct restrictions on cash flow, such as investment decisions, debt issuance, and dividend payment (Kim, Tsui, and Yi 2011), and better mitigate agency conflicts by playing a signaling role (Smith and Warner 1979; Demiroglu and James 2010). This may explain why FCM raises general covenants but not financial covenants. In addition, in Column (4), where *CONVEN_STRICT* is the dependent variable, we observe a significant increase in the strictness of financial covenants.[11] Overall, these findings suggest that banks also intensify the use of non-pricing terms in loan contracts following the reduction of informativeness of futures prices.

[Insert Table 8 about here]

6.3 FCM and Firm Investments

In previous analyses, we document that FCM raises corporate loan spreads by elevating banks' information processing costs and the associated information risks. To gain a deeper insight into the consequences of heightened bank lending costs, we perform further analyses in this section to explore the effects of FCM on firms'

[11] Note that the sample size is reduced in Column (4) of Table 8. This is because the Murfin (2012) method requires data from the previous 12 quarters to compute the likelihood that a covenant will be breached.

investment activities, particularly for those reliant on bank financing.

To examine this question, we construct a variable, *INVESTMENT*, defined as firm's total capital expenditures, investments in intangibles, and acquisitions scaled by its sales, and regress it on *INDEX_DEP×POST* and a set of control variables and fixed effects. The regressions are performed at the borrowing firm level. The results, reported in Column (1) of table 9, reveal a significant negative coefficient of *INDEX_DEP×POST*, suggesting that corporate investments declines after FCM.

To understand the role of banks in the above relation, we split our sample firms into two groups based on their reliance on bank financing. Following Houston and Shan (2022), we define high bank-dependent firms as those that do not have credit ratings. This classification is grounded in the observation that these firms are typically less transparent, hence relying primarily on a few financially capable institutions (such as banks) for funding. We separately conduct the aforementioned regression on these two groups of firms and report the results in Columns (2) and (3) of Table 9. The coefficient of *INDEX_DEP×POST* is negatively significant for the group of firms with high bank dependence, while is insignificant for the other group. The results suggest that the negative impact of FCM on corporate investments is concentrated among firms who are heavily dependent on banks. Taken together, our findings indicate that the raise in borrowing costs attributed to FCM hampers firms' investment behaviors, especially for those that heavily rely on bank financing.

[Insert Table 9 about here]

5. Conclusion

This study highlights the critical role of commodity futures market informativeness in shaping bank loan contracting. Our findings reveal that FCM disrupts the flow of demand and supply information embedded in commodity prices, prompting banks to adjust their loan terms. Specifically, we find that firms with high dependency on index commodities face higher loan spreads, particularly when their banks have limited information channels, they disclose lower-quality financial reports, operate in opaque environments, and have greater default risk. We also find that the intensity and strictness of covenants also rise after FCM. Further, the increase in financing costs has tangible consequences, as investment activities of credit-dependent firms become notably constrained in the post-FCM period.

This study contributes to the literature in several ways. First, it contributes to the bank loan contracting literature by providing evidence that banks incorporate information embedded in commodity markets into the design of loan contracts. Second, it contributes to the literature on information risk in bank lending by identifying the informativeness of futures prices as a novel external source of such risk. Last, it deepens our understanding of FCM's broader economic consequences by focusing on its impact on banks. Additionally, the findings in our study have important policy implications. By showing that FCM generates a negative externality in the form of higher credit costs, we appeal to policymakers and regulators to take into account the broader economic impacts of index investing—particularly its effects on firm-level financing and investment decisions—when assessing the costs and benefits of such market transformations.

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Appendix A. Variable Definition

This Appendix presents definitions of the variables in our analyses. The loan level information is obtained from Thomson Reuters Loan Pricing Corporation (LPC) DealScan database. Control variables at the firm levels are constructed using data from Compustat.

Dependent Variables	
Log(SPREAD)	The natural logarithm of all-in loan spread drawn for each facility obtained. All-in loan spread drawn is defined as the amount the borrower pays in bps over LIBOR or LIBOR equivalent for each dollar drawn down.
Independent Variable	
INDEX_DEP	The amount of index commodities produced or used by an industry divided by its total economic activity, measured as the sum of its inputs and outputs.
NONINDEX_DEP	The amount of non-index commodities produced or used by an industry divided by its total economic activity, measured as the sum of its inputs and outputs.
POST	Indicator variable that is set to one for years between 2005-2007 and zero for 2001-2003.
PREn	Indicator variable that is set to one for the n^{th} year before the onset of FCM (2004), and zero otherwise.
POSTn	Indicator variable that is set to one for the n^{th} year after the onset of FCM (2004), and zero otherwise.
Control Variables	
SIZE	The natural logarithm of the firm's total assets (*at*).
TANGI	Net property, plant, and equipment (*ppent*) divided by total assets (*at*).
CASH	Cash (*ch*) divided by total assets (*at*).
WORKCAP	Working capital (*wcap*) divided by total assets (*at*).
LEV	Book value of long-term debt plus debt in current liabilities (*dltt*+*dlc*), divided by total assets (*at*).
SALESGTH	The growth rate of total sales (*sale*).
CAPX	Capital expenditure (*capx*) divided by total assets (*at*).
R&D	Research and development expenses (*xrd*) divided by total assets (*at*).
ROA	Operating income before depreciation (*oibdp*) divided by total assets (*at*).
OPCF	Operating cash flow (*oancf*) divided by total assets (*at*).
ZSCORE	The modified Altman's (1968) Z-score, which is computed as (1.2×working capital+1.4×retained earnings+3.3×EBIT+0.999×sales) divided by total assets (*at*).
LOANAMOU	The natural logarithm of the amount of a loan facility.
LOANMATU	The natural logarithm of the number of months to maturity of a loan facility.
LOANCOLL	Indicator variable that is set to 1 if the loan is secured by collateral and 0 otherwise.
LOANSYND	Indicator variable that is set to 1 if the loan is a syndicated loan and 0 otherwise.
Other Variables	
BANKSIZE	The natural logarithm of the bank's total assets.
GEOPROX	Indicator variable that is set to one if the firm and the bank are located in the same Metropolitan Statistical Area (MSA) and 0 otherwise.
ACCRQUALITY	The absolute abnormal accruals calculated using the modified Jones model.
CONSERVATISM	Accounting conservatism measure calculated using the Basu (1997) model.
COMPARABILITY	The average of the comparability scores between the firm and its top 10 industry peers. Accounting comparability score is calculated following De Franco et al. (2011).
INFTRADE	Informed trading measured by the Generalized Probability of Information-based Trading (GPIN).
ANALYST	The number of analysts that follow the firm during the year.
MEDIA	The number of news articles about the firm during the year.

DISTDEFAULT	Distance to default measured calculated using the naïve DD model developed by Bharath and Shumway (2008).
CFVOLATILITY	The standard deviation of the ratio of operating cash flow (*oancf*) over total assets (*at*) during the previous five years.
CONVEN_TOTAL	The number of total covenants in the loan contract.
CONVEN_TOTAL	The number of general covenants in the loan contract.
CONVEN_FIN	The number of financial covenants in the loan contract.
CONVEN_STRICT	The likelihood of covenant violation constructed following Murfin (2012).
INVESTMENT	The sum of total capital expenditures (*capx*), investments in intangibles (*xrd*), and acquisitions (*aqc* - *sppe*) divided by total sales (*sale*).

Figure 1: Placebo Test

This figure presents the distribution of the estimated placebo coefficients by randomly assign index commodity dependence to firms. For each iteration, we create a placebo sample through the random allocation and apply our baseline model for estimation on this placebo sample, subsequently documenting the estimated coefficients and *t*-statistics. This process is repeated 1,000 times to generate the distribution of estimated coefficients and *t*-statistics for pseudo-*INDEX_DEP×POST*. The dotted line represents the actual coefficient of *INDEX_DEP×POST* in Column (1) of Table 2.

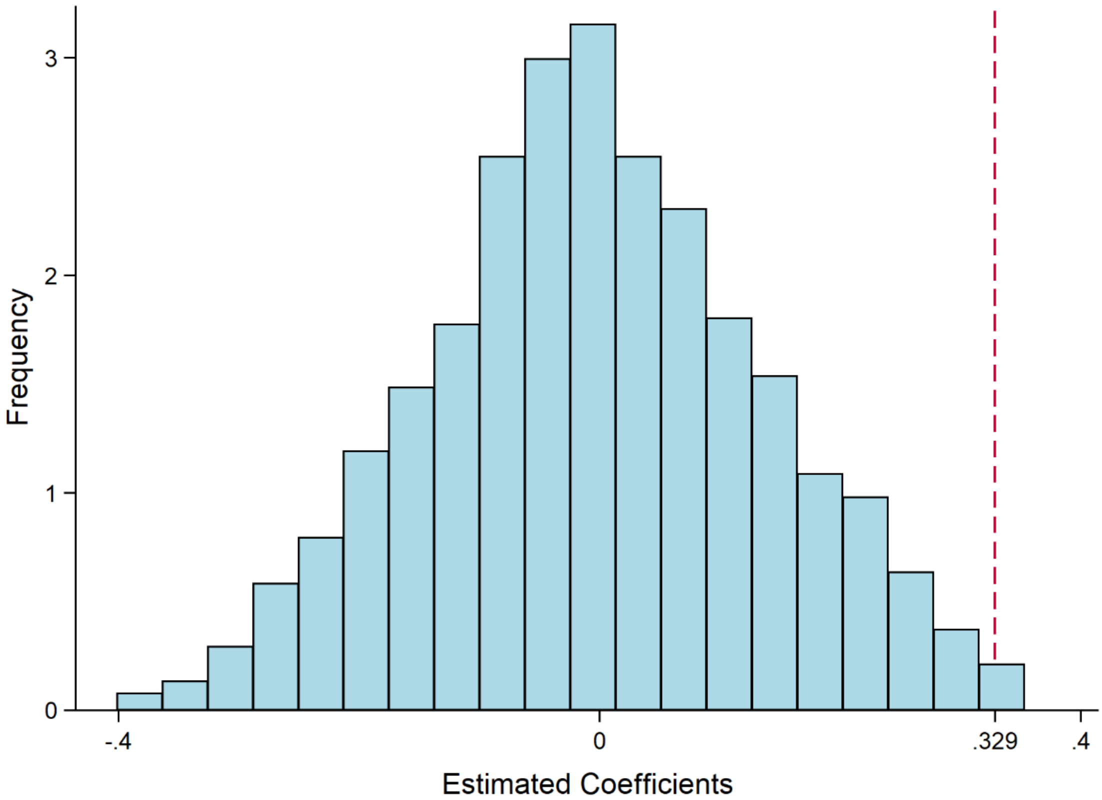

Table 1: Descriptive Statistics

This table presents the summary statistics for variables in the baseline model. The sample contains 11,864 facility-level observations during the six years centered on 2004. *Log(SPREAD)* is the natural logarithm of *SPREAD*, the all-in loan spread obtained from the DealScan database, for a loan facility. *INDEX_DEP* is measured as the amount of index commodities produced or used by an industry divided by its total economic activity (the sum of its inputs and outputs). *POST* is an indicator variable that is set to one for years between 2005-2007 and zero for 2001-2003. The definitions of variables are summarized in Appendix A.

			Percentile		
Variable	Mean	Std. Dev.	25th	50th	75th
Log(SPREAD)	5.022	0.886	4.472	5.298	5.661
INDEX_DEP	0.032	0.106	0.000	0.001	0.003
POST	0.498	0.500	0.000	0.000	1.000
SIZE	7.320	1.880	6.046	7.256	8.615
TANGI	0.308	0.228	0.123	0.253	0.445
CASH	0.065	0.077	0.015	0.038	0.083
WORKCP	0.126	0.160	0.017	0.106	0.214
LEV	0.354	0.238	0.196	0.320	0.469
SALESGTH	0.156	0.334	-0.004	0.086	0.222
CAPX	0.056	0.062	0.020	0.036	0.066
R&D	0.017	0.038	0.000	0.000	0.015
SG&A	0.211	0.206	0.064	0.151	0.295
ROA	0.152	0.114	0.090	0.141	0.203
OPCF	0.103	0.103	0.048	0.097	0.151
ZSCORE	1.441	1.437	0.807	1.476	2.217
LOANAMOU	18.624	1.649	17.622	18.792	19.756
LOANMATU	3.695	0.677	3.497	4.078	4.094
LOANCOLL	0.570	0.495	0.000	1.000	1.000
LOANSYND	0.954	0.210	1.000	1.000	1.000

Table 2: Financialization of Commodity Market and Loan Spread

This table reports the coefficients estimating the effect of financialization of commodity market on loan spread. *Log(SPREAD)* is the natural logarithm of *SPREAD*, the all-in loan spread obtained from the DealScan database, for a loan facility. *INDEX_DEP* is measured as the amount of index commodities produced or used by an industry divided by its total economic activity (the sum of its inputs and outputs). In column (1), *POST* is an indicator variable that is set to one for years between 2005-2007 and zero for 2001-2003. In column (2), *PREn* (*POSTn*) is the n^{th} year before (after) 2004. Definitions of other variables are summarized in Appendix A. Firm-clustered heteroskedasticity-robust t-statistics are reported in parentheses. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

	(1) DID Estimation	(2) Dynamic Analysis
	Log(SPREAD)	*Log(SPREAD)*
INDEX_DEP×POST	0.329***	
	(2.67)	
INDEX_DEP×PRE2		-0.033
		(-0.20)
INDEX_DEP×PRE1		0.243
		(1.36)
INDEX_DEP×POST1		0.488**
		(2.57)
INDEX_DEP×POST2		0.568***
		(2.89)
INDEX_DEP×POST3		0.452**
		(2.21)
SIZE	-0.055**	-0.059**
	(-2.24)	(-2.39)
TANGI	-0.161	-0.165
	(-1.08)	(-1.11)
CASH	-0.039	-0.042
	(-0.22)	(-0.24)
WORKCP	-0.019	-0.017
	(-0.17)	(-0.16)
LEV	0.404***	0.404***
	(6.34)	(6.36)
SALESGTH	0.111***	0.109***
	(4.53)	(4.46)
CAPX	-0.733***	-0.748***
	(-3.12)	(-3.22)
R&D	-0.445	-0.468
	(-0.58)	(-0.61)
SG&A	-0.099	-0.106
	(-0.82)	(-0.88)
ROA	-0.577***	-0.581***
	(-4.33)	(-4.39)
OPCF	-0.091	-0.087
	(-0.75)	(-0.72)
ZSCORE	-0.040***	-0.041***
	(-2.79)	(-2.84)
LOANAMOU	-0.134***	-0.134***
	(-13.99)	(-14.01)
LOANMATU	0.020	0.020
	(1.14)	(1.15)
LOANCOLL	0.258***	0.258***
	(11.13)	(11.13)

LOANSYND	0.098**	0.099**
	(2.45)	(2.46)
CONSTANT	7.715***	7.748***
	(34.49)	(34.40)
Firm FE	YES	YES
Year FE	YES	YES
Loan Type FE	YES	YES
Loan Purpose FE	YES	YES
Observations	11,864	11,864
Adjusted R^2	80.42%	80.44%

Table 3: Robustness Tests

This table reports the robustness tests of the influence of financialization of commodity market on loan spread. In Panel A, we conduct robustness checks using alternative sample periods. Columns (1) and (2) present the results for samples extended to five and eight years, respectively, surrounding the year 2004. In Panel B, we conduct robustness tests utilizing alternative definitions for bank loan spread and index dependence. Specifically, Column (1) presents the results when employing the raw bank loan amount as the dependent variable. Column (2) presents the results using a ranked bank loan spread as the dependent variable, where the raw bank loan spreads are categorized into ten groups annually, and this ranked metric is employed as the dependent variable. Column (3) presents the outcomes when the *INDEX_DEP* is defined at firm level following Brogaard et al. (2019), in which *INDEX_DEP* is an indicator variable assigned a value of 1 if a firm's average count of agricultural, energy, or metals terms in their 10-K reports from 2001 to 2003 ranks in the top decile of the sample's average counts for these terms, and a value of 0 otherwise. Panel C reports the results from a placebo test with *NONINDEX_DEP* constructed using non-index commodity. For all panels, the same set of control variables are included in the estimations. Definitions of other variables are summarized in Appendix A. Firm-clustered heteroskedasticity-robust t-statistics are reported in parentheses. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

Panel A: Robustness tests with alternative sample period

	(1) Sample period expanded as the four- year period centered on 2004	(2) Sample period expanded as the eight-year period centered on 2004
	Log(SPREAD)	*Log(SPREAD)*
INDEX_DEP×POST	0.300***	0.225**
	(2.67)	(2.27)
CONTROLS	YES	YES
Firm FE	YES	YES
Year FE	YES	YES
Loan Type FE	YES	YES
Loan Purpose FE	YES	YES
Observations	15,041	26,115
Adjusted R^2	78.68%	75.04%

Panel B: Robustness test with alternative definition of bank loan spared and index dependence

	(1) Raw loan spread	(2) Ranked loan spread	(3) Index dependence defined at firm level
	SPREAD	*Rank(SPREAD)*	*Log(SPREAD)*
INDEX_DEP×POST	97.031***	1.355***	0.116***
	(3.63)	(2.83)	(3.21)
CONTROLS	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Loan Type FE	YES	YES	YES
Loan Purpose FE	YES	YES	YES
Observations	11,864	11,864	11,864
Adjusted R^2	66.52%	75.24%	80.45%

Panel C: Placebo test with non-index commodity dependence

	(1)
	Log(SPREAD)
NONINDEX_DEP×POST	0.011
	(0.05)
CONTROLS	YES
Firm FE	YES
Year FE	YES
Loan Type FE	YES
Loan Purpose FE	YES
Observations	11,864
Adjusted R^2	80.39%

Table 4: Influence of Richness of Bank's Information Channels

This table reports the cross-sectional results of the influence of bank's information acquisition capability on the relationship between financialization of commodity market and loan spread. *Log(SPREAD)* is the natural logarithm of *SPREAD*, the all-in loan spread obtained from the DealScan database, for a loan facility. *INDEX_DEP* is measured as the amount of index commodities produced or used by an industry divided by its total economic activity (the sum of its inputs and outputs). *POST* is an indicator variable that is set to one for years between 2005-2007 and zero for 2001-2003. In Column (1) and (2), bank size is measured by the value of its total assets. We divided the sample into two subsamples based on the median bank size in our sample. In column (3) and (4), we define the geographic proximity between the borrower and lender as high (low) if they are in the same (different) MSA. The same set of control variables is included in all models but are not tabulated for brevity. Definitions of other variables are summarized in Appendix A. Firm-clustered heteroskedasticity-robust t-statistics are reported in parentheses. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

	(1)	(2)	(3)	(4)
Partition Variable:	*BANKSIZE*		*GEOPROXIMITY*	
	Large	Small	High	Low
	Log(SPREAD)	*Log(SPREAD)*	*Log(SPREAD)*	*Log(SPREAD)*
INDEX_DEP×POST	-0.042	0.607***	-0.098	0.359**
	(-0.23)	(3.86)	(-0.43)	(2.38)
CONTROLS	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Loan Type FE	YES	YES	YES	YES
Loan Purpose FE	YES	YES	YES	YES
Observations	3,435	8,396	3,255	8,576
Adjusted R^2	84.25%	80.57%	80.36%	81.40%
Difference: p-value	0.003		0.047	

Table 5: Influence of Borrower's Financial Reporting Quality

This table reports the cross-sectional results of the influence of borrower's financial reporting quality on the relationship between financialization of commodity market and loan spread. *Log(SPREAD)* is the natural logarithm of *SPREAD*, the all-in loan spread obtained from the DealScan database, for a loan facility. *INDEX_DEP* is measured as the amount of index commodities produced or used by an industry divided by its total economic activity (the sum of its inputs and outputs). *POST* is an indicator variable that is set to one for years between 2005-2007 and zero for 2001-2003. In column (1) and (2), accounting quality is measured as the absolute abnormal accruals calculated using the modified Jones model. In column (3) and (4), accounting conservatism is calculated using Basu (1997) model over our sample period. In column (5) and (6), accounting comparability is constructed following De Franco et al. (2011). In all tests, we divided the sample into two subsamples based on the annual median of the respective variable. The same set of control variables is included in all models but are not tabulated for brevity. Definitions of other variables are summarized in Appendix A. Firm-clustered heteroskedasticity-robust t-statistics are reported in parentheses. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Partition Variable:	*ACCRQUALITY*		*CONSERVATISM*		*COMPARABILITY*	
	High *Log(SPREAD)*	Low *Log(SPREAD)*	High *Log(SPREAD)*	Low *Log(SPREAD)*	High *Log(SPREAD)*	Low *Log(SPREAD)*
INDEX_DEP×POST	0.106	0.537***	0.101	0.541***	0.304	1.268***
	(0.50)	(3.45)	(0.58)	(3.23)	(1.61)	(3.82)
CONTROLS	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Loan Type FE	YES	YES	YES	YES	YES	YES
Loan Purpose FE	YES	YES	YES	YES	YES	YES
Observations	5,703	5,718	4,525	4,711	3,591	3,579
Adjusted R^2	82.45%	80.70%	80.74%	80.31%	81.77%	80.47%
Difference: p-value	0.049		0.035		0.006	

Table 6: Influence of Borrower's Information Environment

This table reports the cross-sectional results of the influence of borrower's information environment on the relationship between financialization of commodity market and loan spread. *Log(SPREAD)* is the natural logarithm of *SPREAD*, the all-in loan spread obtained from the DealScan database, for a loan facility. *INDEX_DEP* is measured as the amount of index commodities produced or used by an industry divided by its total economic activity (the sum of its inputs and outputs). *POST* is an indicator variable that is set to one for years between 2005-2007 and zero for 2001-2003. In column (1) and (2), informed trading is measured by the Generalized Probability of Information-based Trading (GPIN) value, which is the annual median of daily GPIN for a given year. We thank Professor Duarte for sharing the GPIN data (Duarte et al. 2020). In column (3) and (4), analyst coverage is measured by the number of analysts who covers the firm each year. In column (5) and (6), media coverage is measured by the number of news articles a company receives each year. In all tests, we divided the sample into two subsamples based on the annual median of the respective variable. The same set of control variables is included in all models but are not tabulated for brevity. Definitions of other variables are summarized in Appendix A. Firm-clustered heteroskedasticity-robust t-statistics are reported in parentheses. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Partition Variable:	*INFTRADE*		*ANALYST*		*MEDIA*	
	High	Low	High	Low	High	Low
	Log(SPREAD)	*Log(SPREAD)*	*Log(SPREAD)*	*Log(SPREAD)*	*Log(SPREAD)*	*Log(SPREAD)*
INDEX_DEP×POST	0.609**	0.165	0.208	0.642***	0.154	0.687***
	(2.35)	(0.73)	(1.33)	(2.98)	(1.05)	(3.97)
CONTROLS	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Loan Type FE	YES	YES	YES	YES	YES	YES
Loan Purpose FE	YES	YES	YES	YES	YES	YES
Observations	1,871	1,877	7,750	4,114	5,505	5,874
Adjusted R^2	84.29%	84.51%	81.46%	79.35%	82.92%	77.60%
Difference: p-value	0.092		0.052		0.010	

Table 7: Influence of Borrower's Default Risk

This table reports the cross-sectional results of the influence of default risk on the relationship between financialization of commodity market and loan spread. *Log(SPREAD)* is the natural logarithm of *SPREAD*, the all-in loan spread obtained from the DealScan database, for a loan facility. *INDEX_DEP* is measured as the amount of index commodities produced or used by an industry divided by its total economic activity (the sum of its inputs and outputs). *POST* is an indicator variable that is set to one for years between 2005-2007 and zero for 2001-2003. In column (1) and (2), we use Altman's Z-score to measure the firm's default risk. In column (3) and (4), distance to default is measured using the naïve DD model proposed by Bharath and Shumway (2008). In column (5) and (6), default risk is measured by the operating cash flow volatility of the firm over previous five years. In all tests, we divided the sample into two subsamples based on the annual median of the respective variable. The same set of control variables is included in all models but are not tabulated for brevity. Definitions of other variables are summarized in Appendix A. Firm-clustered heteroskedasticity-robust t-statistics are reported in parentheses. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Partition Variable:	*ZSCORE*		*DISTDEFAULT*		*CFVOLATILITY*	
	High *Log(SPREAD)*	Low *Log(SPREAD)*	High *Log(SPREAD)*	Low *Log(SPREAD)*	High *Log(SPREAD)*	Low *Log(SPREAD)*
INDEX_DEP×POST	0.097	0.457***	0.070	0.593***	0.551***	0.143
	(0.47)	(2.66)	(0.29)	(3.22)	(3.40)	(0.69)
CONTROLS	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Loan Type FE	YES	YES	YES	YES	YES	YES
Loan Purpose FE	YES	YES	YES	YES	YES	YES
Observations	5,938	5,926	4,542	4,531	5,532	5,514
Adjusted R^2	82.39%	78.57%	77.15%	83.01%	77.62%	84.05%
Difference: p-value	0.091		0.042		0.061	

Table 8: Financialization of Commodity Market and Loan Covenants

This table reports the coefficients estimating the effect of financialization of commodity market on loan covenants. *CON_TOTAL* (*CON_GEN* and *CON_FIN*) is the number of total (general and financial) covenants in the loan contract. *CON_STRICT* is the strictness of financial covenants measuring the likelihood of covenant violation following Murfin (2012). *INDEX_DEP* is measured as the amount of index commodities produced or used by an industry divided by its total economic activity (the sum of its inputs and outputs). *POST* is an indicator variable that is set to one for years between 2005-2007 and zero for 2001-2003. Definitions of other variables are summarized in Appendix A. Firm-clustered heteroskedasticity-robust t-statistics are reported in parentheses. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

	(1) *CONVEN_TOTAL*	(2) *CONVEN_GEN*	(3) *CONVEN_FIN*	(4) *CONVEN_STRICT*
INDEX_DEP×POST	1.123**	0.820**	0.295	0.242***
	(2.10)	(2.15)	(1.15)	(3.74)
SIZE	0.318*	0.244**	0.076	-0.054***
	(1.92)	(2.12)	(1.09)	(-2.89)
TANGI	-1.177	-0.863	-0.330	-0.253**
	(-1.33)	(-1.34)	(-0.88)	(-2.38)
CASH	-0.871	-0.136	-0.743	0.055
	(-0.76)	(-0.17)	(-1.56)	(0.45)
WORKCP	0.767	0.468	0.302	-0.181**
	(1.16)	(1.02)	(1.05)	(-2.15)
LEV	1.740***	1.660***	0.077	0.212***
	(4.30)	(5.68)	(0.48)	(4.34)
SALESGTH	-0.064	-0.030	-0.028	0.060**
	(-0.28)	(-0.20)	(-0.29)	(2.37)
CAPX	-2.074	-1.901*	-0.140	-0.134
	(-1.43)	(-1.91)	(-0.21)	(-0.80)
R&D	-3.266	-2.181	-1.140	-0.420
	(-0.82)	(-0.73)	(-0.80)	(-0.76)
SG&A	-0.322	-0.180	-0.138	0.170*
	(-0.47)	(-0.35)	(-0.45)	(1.68)
ROA	1.185	0.318	0.868*	-0.662***
	(1.13)	(0.45)	(1.96)	(-5.45)
OPCF	-0.648	-0.401	-0.266	0.066
	(-0.73)	(-0.64)	(-0.74)	(0.70)
ZSCORE	0.013	-0.043	0.054	-0.011
	(0.13)	(-0.60)	(1.52)	(-0.82)
LOANAMOU	0.205***	0.111***	0.093***	-0.009***
	(6.29)	(4.85)	(6.57)	(-3.09)
LOANMATU	0.129	0.105*	0.029	-0.005
	(1.45)	(1.68)	(0.73)	(-0.47)
LOANCOLL	2.130***	1.405***	0.729***	0.063***
	(17.38)	(16.53)	(13.55)	(4.03)
LOANSYND	0.505***	0.366***	0.134*	-0.024
	(2.95)	(3.10)	(1.70)	(-0.95)
CONSTANT	-5.061***	-3.536***	-1.525**	0.911***
	(-3.62)	(-3.59)	(-2.54)	(5.90)
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Loan Type FE	YES	YES	YES	YES
Loan Purpose FE	YES	YES	YES	YES
Observations	11,864	11,864	11,864	6,595
Adjusted R^2	63.04%	63.08%	58.49%	68.83%

Table 9: Financialization of Commodity Market, Bank Dependence and Corporate Investment

This table reports the joint effects of financialization of commodity market and bank dependence on corporate investment. *INVESTMENT* is total capital expenditures, investments in intangibles, and acquisitions scaled by sales. *INDEX_DEP* is measured as the amount of index commodities produced or used by an industry divided by its total economic activity (the sum of its inputs and outputs). *POST* is an indicator variable that is set to one for years between 2005-2007 and zero for 2001-2003. Following Houston and Shan (2022), we define a firm as high bank-dependent firm if it doesn't have credit rating. Definitions of other variables are summarized in Appendix A. Firm-clustered heteroskedasticity-robust t-statistics are reported in parentheses. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

	(1) Full Sample	(2) High Bank Dependence	(3) Low Bank Dependence
	INVESTMENT	*INVESTMENT*	*INVESTMENT*
INDEX_DEP×POST	-0.279**	-0.417***	-0.011
	(-2.57)	(-2.75)	(-0.37)
SIZE	0.088***	0.095**	0.032
	(2.59)	(2.39)	(1.43)
TANGI	0.331	0.401	0.002
	(1.51)	(1.62)	(0.02)
CASH	0.162	0.187	-0.216
	(0.84)	(0.92)	(-1.57)
WORKCP	0.044	0.051	0.040
	(0.63)	(0.71)	(1.37)
LEV	0.102	0.120	-0.046
	(1.11)	(1.20)	(-1.24)
SALESGTH	-0.148***	-0.159***	0.041
	(-6.21)	(-6.41)	(0.78)
ROA	-0.208**	-0.209**	0.153
	(-1.99)	(-1.98)	(1.38)
OPCF	-0.326***	-0.333***	0.034
	(-2.78)	(-2.79)	(0.46)
ZSCORE	-0.000	-0.000	-0.037***
	(-0.10)	(-0.09)	(-3.08)
CONSTANT	-0.126	-0.011	-0.141
	(-0.66)	(-0.06)	(-0.62)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	33,562	26,291	7,271
Adjusted R^2	51.93%	50.59%	71.94%
Difference: p-value		0.005	