Real Effects of Centralized Markets: Evidence from Steel Futures*

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Abstract

I study the real effects of centralized derivative markets using the staggered introduction of futures contracts for different steel products in the U.S. Employing a difference-in-differences strategy, I find that the arrival of centralized futures markets improves price transparency and risk management in the underlying product market: price dispersion decreases and steel producers increase their hedging activity. Moreover, market share is reallocated toward low-cost producers, while product prices, producers' profits, and valuations decrease. Overall, the results indicate that centralized futures markets foster competition in the product market.

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1 Introduction

Over the past two decades, exchange-trading of derivatives has experienced significant growth, with the number of contracts worldwide rising from 3 billion in 2001 to 41 billion in 2020. This trend intensified after the financial crisis of 2007–2008, which led regulators globally to advocate for the migration of derivative trading from over-the-counter (OTC) markets to centralized exchanges.[1] Over the same period, commodity futures have become the most actively traded derivative product on exchanges, expanding from 110 million to 8 billion contracts (World Federation of Exchanges, 2020). Recent studies indicate that centralization enhances liquidity, reduces trading costs, and diminishes dealer markups in financial markets (e.g., Biais and Green, 2019; O'Hara and Zhou, 2021; Allen and Wittwer, 2023). However, whether the centralization of derivative markets affects the underlying product markets remains an open question.

Theory suggests that centralized derivative markets impact the underlying product markets via two main channels: price information and risk management. First, centralization creates public price signals, improving market participants' information (Hayek, 1945; Baumol, 1965; Grossman, 1976; Black, 1976). This enhances market search (Stigler, 1961), enabling buyers in the physical product market to negotiate prices more effectively with sellers, hence increasing competition. According to this reference price channel, introducing a centralized derivative market should reduce price dispersion in the underlying product market, increase the market share of low-cost firms, and reduce price levels (Duffie, Dworczak, and Zhu, 2017). The second mechanism underscores the role of centralization for risk management. Centralized markets may enhance firms' ability to manage price risk by increasing liquidity or lowering counterparty risk (Telser and

[1] In 2009, G20 Leaders agreed that "all standardized OTC derivative contracts should be traded on exchanges or electronic trading platforms" (Financial Stability Board, 2017).

Higinbotham, 1977; Telser, 1981). Conversely, price information generated by the centralized market may diminish risk-sharing opportunities and make it harder for firms to manage risk (Hirshleifer, 1971; Goldstein and Yang, 2022). Thus, the net effect on firms' risk management depends on which of these opposing forces dominates. In the presence of financial frictions, risk management in turn mitigates underinvestment due to insufficient internal funds (Froot, Scharfstein, and Stein, 1993). In markets with a sticky customer base, lowering prices to gain market share is a form of investment in customer capital (Klemperer, 1987). By stabilizing cash flows, effective risk management enables otherwise liquidity-constrained firms to set lower prices and compete more aggressively for market share (Chevalier and Scharfstein, 1996).

To date, there is no evidence that centralized derivative markets have such important real effects. The main challenge in addressing this question is that the introduction of a centralized derivatives market may depend on market conditions and occur contemporaneously with other events, which may confound the effects. To address these issues, I rely on the close-to-ideal setting of the U.S. steel futures market. Before the arrival of centralized steel futures markets, sellers and buyers in the physical steel market could hedge price risk with decentralized OTC forward contracts.[2] The New York Mercantile Exchange (NYMEX) introduced steel futures contracts targeted at the U.S. market for hot-rolled coils (HRC) in 2008 and for busheling scrap (BUS) in 2012. I employ a difference-in-differences (DiD) strategy and compare hot-rolled coils and busheling scrap to a set of control steel products that were initially candidates for futures trading in the U.S., before and after the respective futures began trading. Importantly, this strategy controls for common shocks hitting all steel products. The key identification assumption is that treated and control steel products would have trended similarly in the absence of the futures market. Three key facts support this parallel

[2]Forwards are bilaterally negotiated contracts regarding the future exchange of an underlying asset at the specified price. Futures are standardized forward contracts traded on centralized exchanges.

trends assumption. First, treated and control products are ex-ante comparable in terms of volatility, a key requirement for the viability of futures contracts. They also exhibit similar cyclicality, mitigating concerns that differential business cycle effects confound the estimation. Second, treated and control products exhibit parallel trends before the introduction of the NYMEX futures. Likewise, outcomes of firms selling treated products in the U.S. show similar trends to control producers before the arrival of the futures markets. Third, placebo tests demonstrate that parallel trends continue to hold for non-U.S. firms after the NYMEX futures introductions: outcomes of firms selling treated products outside the U.S. show no divergent evolution compared to control producers.

I start the empirical analysis by exploring the key prediction of the reference price channel. Steel products are not traded on centralized spot markets. Instead, product market prices are negotiated bilaterally between producers and their customers for delivery in 1 to 12 months. When steel futures began trading, industry participants could now observe market prices for the traded products for up to three years ahead, discovered on a centralized exchange. Ample anecdotal evidence suggests that futures prices serve as reference prices in negotiations between sellers and buyers of steel in the physical product market. In search and bargaining models, the availability of reference prices lowers the equilibrium price dispersion (Janssen, Pichler, and Weidenholzer, 2011; Duffie, Dworczak, and Zhu, 2017; Grennan and Swanson, 2020). I measure price dispersion across different reporting firms for the same product at a given point in time, using proprietary data on firms' reported prices for six steel products bought in the U.S. from 2007 to 2017. Price dispersion in the steel market was substantial before the arrival of the futures markets, with a coefficient of variation of 19%.[3] Consistent with the futures markets providing reference prices for the product market,

[3]Grennan and Swanson (2020) document a coefficient of variation of 18% in the market for hospital supplies, which they place close to the top of the range documented in consumer goods markets. They argue that business-to-business settings often

I find that price dispersion decreases by 6 percentage points for treated relative to control products after the introduction of steel futures. Importantly, treated and control products follow parallel trends before the introduction, supporting a causal interpretation.

Next, I investigate whether the arrival of the centralized futures markets affects the risk management of firms selling treated products. I utilize information disclosed in annual reports of publicly traded firms headquartered in the U.S. to identify firms' products and usage of commodity derivatives.[4] I find that firms selling treated products increase their commodity hedging relative to control producers. Treated firms are more likely to discuss the use of commodity derivatives in their annual report. Furthermore, profits of treated firms become less correlated with steel prices, consistent with futures markets enabling producers to isolate their profits from steel price risk more effectively. Thus, I find support for increased price transparency and improved risk management in the data. As a result, competition in the product market should increase.

To test for competitive effects in the product market, I first examine the sensitivity of market shares to costs. The availability of reference prices enables buyers to identify low-cost producers more effectively, thereby increasing the sensitivity of market shares to production costs (Duffie, Dworczak, and Zhu, 2017). Improved risk management allows producers to compete more aggressively (Froot, Scharfstein, and Stein, 1993; Chevalier and Scharfstein, 1996), enhancing low-cost producers' ability to capture market share. To test this prediction, I leverage the fact that raw steel is made either from iron ore, using basic oxygen furnaces (BOF), or from steel scrap, using electric arc furnaces (EAF). The relative cost advantage of these two production technologies depends on iron ore and scrap prices. After the introduction of hot-rolled coil

lack transparency: Negotiated prices vary widely across buyers, and buyers have typically limited information about other buyers' contracts.

[4]These firms represent about two thirds of the 100 billion USD worth of steel shipments in the U.S. in 2007.

futures, the market share of treated producers who primarily use scrap increases more significantly when scrap becomes cheaper relative to iron ore. Specifically, treated EAF producers gain 0.5 to 0.8 percentage points more market share with a 10% increase in the iron ore-to-scrap price ratio compared to control producers. Thus, market shares become more sensitive to costs after the arrival of the futures market.

Next, I analyze the effect on product prices. The availability of reference prices prompts sellers to reduce markups (Janssen, Pichler, and Weidenholzer, 2011; Duffie, Dworczak, and Zhu, 2017), resulting in lower prices. Furthermore, improved risk management enables firms that would otherwise be liquidity-constrained to invest in market share by lowering prices (Froot, Scharfstein, and Stein, 1993; Chevalier and Scharfstein, 1996). Additionally, the reallocation of market shares toward low-cost producers further drives down prices. Confirming this prediction, I find that prices of treated products decrease by 4% relative to control products after the introduction of the futures market.

Finally, I study the effects on producers. Increased product market competition should lead to lower operating profits for firms selling the treated products. However, public price information generated by the futures market could also help producers make better production decisions, which should increase their operating profits (Goldstein and Yang, 2022). I find that operating profits, scaled by lagged assets, of firms selling treated products in the physical market drop by 1 to 2 percentage points relative to control firms. Furthermore, I find that stock prices of treated producers decrease by 4% to 5% relative to control producers around the arrival of news that increases the likelihood of a futures contract. This aligns with investors anticipating a decrease in producer profits resulting from the futures market. Taken together, the results are consistent with futures markets increasing competition in the product market.

A natural concern in this setting is that the results may be confounded by other events occurring simultaneously. In particular, the financial crisis of 2007–2008 might have affected treatment and control groups differently. Additionally, many commodities, including steel, experienced a boom-bust cycle in 2008. I conduct a battery of tests to ensure the results are not driven by these events. Most notably, using only the 2012 introduction of busheling scrap futures and excluding the crisis period altogether yields similar results. Furthermore, treated products do not exhibit a stronger decline in quantities, as would be expected if confounding events had reduced demand more for treated products. Similarly, treated products and firms do not differ ex-ante in their exposure to aggregate economic activity or key steel-consuming sectors, such as the automotive or construction industry. Finally, firms selling treated products outside the U.S. show no differential evolution compared to control firms around the introduction of the NYMEX futures markets targeting the U.S. These placebo tests mitigate concerns that other events coinciding with the futures introductions might have differentially affected treated and control producers.

Collectively, the findings indicate that centralized futures markets for steel products enhance competition in the underlying product market by improving price transparency and risk management. Since modern futures contracts typically share the key features of price discovery and central clearing, these findings may extend to other industries with similar market structure. Specifically, futures markets could foster competition in sectors characterized by price dispersion or a sticky customer base (i.e., customer markets). Given that many business-to-business markets lack price transparency (Grennan and Swanson, 2020) and customer markets are widespread in the U.S. economy (Foster, Haltiwanger, and Syverson, 2008, 2016; Hottman, Redding, and Weinstein, 2016), futures markets could increase competition in various sectors. Indeed, according to the World Bank, many major commodity markets rely on futures prices as benchmarks, providing price transparency and enabling effective risk management (Baffes and Nagle, 2022).

This paper contributes to the growing literature on financial market centralization (Barclay, Hendershott, and Kotz, 2006; Hendershott and Madhavan, 2015; Fleming, Mizrach, and Nguyen, 2018; Abudy and Wohl, 2018; Biais and Green, 2019; Benos, Payne, and Vasios, 2020; O'Hara and Zhou, 2021; Allen and Wittwer, 2023) by shifting the focus to implications for the real economy. Specifically, this study documents how the arrival of centralized futures markets for steel affects prices, allocation of market share, and producing firms in the physical product market.

Few existing studies document the real effects of financial market innovation.[5] Pérez-González and Yun (2013) find that the arrival of OTC weather derivatives enabled energy utilities to manage risk more effectively, increasing firm value and investment. Brogaard, Dimitrova, and Eswar (2019) document that the adoption of common standards among OTC currency swap dealers allowed firms to decrease cash-flow volatility and increase patenting activity.[6] Vuillemey (2020) finds that the arrival of central clearing for coffee futures in 1882 reduced traders' counterparty risk and shifted coffee trade flows. To the best of my knowledge, this study is the first to examine the effect of financial market innovation on prices and market

[5]There is also extensive literature studying the relationship between derivative markets and spot markets (Figlewski, 1981; Edwards, 1988a,b; Conrad, 1989; Harris, 1989; Skinner, 1989; Detemple and Jorion, 1990; Stoll and Whaley, 1990; Chan, Chan, and Karolyi, 1991; Damodaran and Lim, 1991; Bessembinder and Seguin, 1992; Jegadeesh and Subrahmanyam, 1993; Chol and Subrahmanyam, 1994; Brenner, Subrahmanyam, and Uno, 1994; Kumar, Sarin, and Shastri, 1998; Mayhew, 2000; Gulen and Mayhew, 2000; Mayhew and Mihov, 2004; Ismailescu and Phillips, 2011; Das, Kalimipalli, and Nayak, 2014; Augustin, Rubtsov, and Shin, 2023).

[6]Related work links firm investment and patenting to trading in equity options and credit default swaps (CDS). Roll, Schwartz, and Subrahmanyam (2009) find a positive relationship between option trading and firm value and investment sensitivity to stock prices. Blanco and Wehrheim (2017) show that option trading predicts increased patenting activity, while Danis and Gamba (2018) and Chang et al. (2019) find that CDS trading is associated with higher investment and patenting, respectively.

share allocation across firms in the product market. Furthermore, by providing evidence that centralized futures markets increase competition in product markets, I document an important channel through which financial market innovation can affect the real economy.

This paper also contributes to the broader literature on real effects of financial markets. Most of the empirical literature focuses on how information contained in stock prices affects firms' investment decisions (Chen, Goldstein, and Jiang, 2007; Foucault and Frésard, 2012; Edmans, Goldstein, and Jiang, 2012; Zuo, 2016; Edmans, Jayaraman, and Schneemeier, 2017; Dessaint et al., 2019).[7] Closest to this paper, Brogaard, Ringgenberg, and Sovich (2019) find that passive investing reduces the informational content of *existing* futures prices in the context of commodity financialization, leading to worse production decisions and lower profits for firms exposed to these commodities. In contrast, this study finds that the *creation* of centralized futures markets decreases price dispersion in the product market as well as prices, producer profits and valuations, while increasing the sensitivity of market share to costs. This suggests that futures markets enhance competition in the product market. To the extent that the financialization of commodity markets spurred an increase in commodity futures creation, this paper documents an important side effect of financialization.[8]

Finally, the price dispersion and producer profit results align with evidence showing that increased transparency in the U.S. corporate bond market reduced price dispersion and dealer profits (Bessembinder, Maxwell, and Venkataraman, 2006; Edwards, Harris, and Piwowar, 2007; Goldstein, Hotchkiss, and Sirri, 2007; Asquith, Covert, and Pathak, 2019), as well as with evidence that price benchmarking services decrease price dispersion in business-to-business markets (Grennan and Swanson, 2020).

[7] See also Bond, Edmans, and Goldstein (2012) for a survey of this literature.

[8] See Cheng and Xiong (2014) for a survey and Goldstein and Yang (2022) for a unified theory of commodity financialization.

2 Institutional Background

This section describes the growth of exchange-traded derivatives and provides information on steel production processes, products, and the arrival of steel futures, which are relevant to the development of hypotheses and the empirical design of this study.

2.1 Exchange-trading of Derivatives

Exchange-traded derivatives have grown significantly over the past two decades. Figure 1 shows that the trading volume of derivative products on exchanges surged from 3 billion contracts in 2001 to 41 billion contracts in 2020. Notably, the trading volume of commodity futures increased from 110 million contracts to 8 billion contracts during this period, raising their share of total derivative trading from 4% to 20%. This increase in trading volume was accompanied by a broader range of commodities being traded on exchanges.[9] These trends underscore the growing significance of exchange-traded derivatives overall, particularlycommodity futures.

[Figure 1 around here.]

2.2 Steel Industry

2.2.1 Production Technology and Cost Advantages

Raw steel can be produced using two different technologies: i) basic oxygen furnaces (BOF) that use iron ore, coal, limestone, and 25-35% steel scrap, and ii) electric arc furnaces (EAF) that use 100% steel scrap. In 2001, 53% of U.S. steel was produced using BOFs and 47% in EAFs (Rogers, 2009). Both technologies

[9] Internet Appendix Figure A.1 shows the increase in distinct commodities covered by the CFTC Commitment of Traders report.

exhibited similar productivity in 2002 (Collard-Wexler and De Loecker, 2015). In the empirical tests, I leverage information on firms' production technology, combined with fluctuating prices of iron ore versus scrap, to measure firms' time-varying cost advantages.

2.2.2 Production Process and Products

Both technologies produce molten steel that can be solidified into semifinished products of various shapes, such as blooms, billets, slabs, and thin slabs.[10] These can be reheated and processed through casting, forging, or rolling. Slabs and thin slabs are processed into plates, pipes, and hot-rolled sheets and coils. Hot-rolled coils (HRC) can be further processed into pickled and oiled coils, cold-rolled coils (CRC) and sheets, and coated coils. Blooms and billets are processed into seamless tubes, structural products, bars, and rods. Figure C.1 in the Internet Appendix presents a flow chart of the steel production process.

These steel products have distinct physical, chemical, and environmental properties tailored to specific applications. As such, customers cannot readily substitute between steel products. For instance, the automotive industry uses HRCs for parts requiring strength and formability. CRCs are used for high-surface-finish components, while standard plates provide stability for reinforcement parts. These properties are achieved through specialized production lines, making it costly for steel producers to switch between products (Collard-Wexler and De Loecker, 2015). Importantly, all steel products are used in multiple steel-consuming sectors (AISI, 2020).[11] These features lay the foundation for the difference-in-differences anal-

[10] Ingots are another semifinished product that can be processed into billets or slabs. The modern continuous casting process bypasses the ingot stage, improving quality and reducing costs.

[11] For instance, construction and machinery use all types of steel products. Automotive and appliances use various sheets, plates, bars, and rods (AISI, 2020).

ysis, enabling the comparison of products with futures trading to similar steel products before and after the arrival of futures markets.

2.3 Steel Futures

In the early 2000s, several exchanges began to consider launching futures markets for various steel products. Internet Appendix C.2 lists the futures contracts introduced for steel products globally up to the end of the sample period in 2017. Due to substantial transportation costs for steel products and other trade barriers, the steel market is geographically segmented, causing prices for the same steel product to vary widely across regions.[12]

In this paper, I leverage price data for steel products bought and sold in the U.S. physical product market. I therefore focus on the effect of futures introductions designed for the U.S. steel market. NYMEX introduced hot-rolled coil (HRC) futures contracts in October 2008 and busheling scrap (BUS) futures in September 2012, both targeting the U.S. market. Next, I outline the details of the NYMEX steel futures, emphasizing how their arrival altered the information environment and risk management opportunities for firms operating in the U.S. product market. These facts guide the hypothesis development in the following section.

The NYMEX HRC and BUS futures contracts are cash-settled, meaning the futures markets did not become an alternative venue to buy physical steel. NYMEX was acquired by CME Group in 2008. Both

[12]For instance, HRC was selling for an average price of 981 USD per ton in the U.S. and 458 USD in China right before the HRC introduction (Source: *Steelbenchmarker*). A key determinant of transportation cost is the weight-to-value ratio (Hummels, 2007; Barrot, Loualiche, and Sauvagnat, 2019). During the sample period, the average shipping cost and weight-to-value ratio for steel products were in the top quartile among traded goods (see Schott, 2008, for a description of the underlying data).

HRC and BUS futures are traded on Globex, the electronic trading platform for CME Group's central limit order book. Traders on Globex can observe the order book and execution prices in real time. Additionally, CME's central counterparty (CCP) clearinghouse guarantees all trades conducted on the Globex platform (CME Group, 2022).

In contrast, before the arrival of centralized futures markets, industry participants had to rely on bilateral forward contracts to manage steel price risk. Prices of these bilateral contracts were privately negotiated and thus unobservable to other industry participants. Moreover, such OTC forward contracts are not guaranteed by a CCP and are typically less liquid than futures contracts. Therefore, managing steel price risk before the arrival of the futures markets involved counterparty and liquidity risk. Consequently, the two key innovations brought about by the centralized futures markets were an increase in public price information and changes in firms' risk management options.[13]

3 Hypotheses

This section presents hypotheses on how changes brought about by the arrival of NYMEX steel futures affect the underlying physical product market.

[13]Existing futures for steel products targeting markets outside the U.S. were unlikely suitable information sources or hedging tools for buyers and sellers in the U.S. product market due to geographic segmentation. Steel imports from regions covered by these earlier futures accounted for only about 2% of the U.S. market. Additionally, these earlier futures did not attract sufficient trading volumes and were eventually suspended. Table A.1 shows that while changes in NYMEX HRC (BUS) futures prices predict changes in hot-rolled coil (busheling scrap) prices in the U.S. product market, the price changes of the earlier futures do not.

3.1 Product Market Effects

3.1.1 Public Price Information as Reference Price

Black (1976) argues that the main benefit of futures markets is generating public and forward-looking price information. When the NYMEX steel futures began trading, U.S. steel market participants were able to observe market prices for contracts with maturities of up to three years ahead, discovered on a centralized exchange. Further, high transportation and warehousing costs pose challenges to physical delivery mechanisms for steel products. As a result, the creation of the futures market spurred the establishment of reliable price indices for the cash settlement of the futures contracts (WSJ, 2004). The creation of the NYMEX futures market thus increased public information about both spot and future prices for the traded steel products in the U.S.[14]

Physical steel products are not traded on centralized spot markets. Instead, prices in the physical product market are negotiated bilaterally between producers and customers, typically for delivery in 1–12 months. Such business-to-business settings often lack transparency. Buyers typically have limited information about other buyers' contracts and negotiate widely varying prices (Grennan and Swanson, 2020). According to Stigler (1961), who coined the term *search* for the process by which buyers ascertain prices in decentralized markets, "price dispersion is a manifestation – and, indeed, it is the measure – of ignorance in the market."

[14]While the CRU Group provided the first price assessment of HRC already in 1980, the price index used for settling the HRC contract shifted to a transaction-only methodology right before HRC futures trading began (CRU Group, 2021). The index changed from monthly to weekly shortly after HRC futures started trading (Newswire, 2013a), and the CRU Group became the first price reporting agency for commodities to be audited by a third-party auditing firm (Newswire, 2013b). The American Metal Market (AMM) index to settle the BUS futures was launched shortly before BUS futures trading began. Finally, survey evidence indicates that serving as an index for a widely traded financial derivative increases the credibility of the price index (CRU Group, 2019).

Before the arrival of futures markets, price dispersion was substantial, with a coefficient of variation of 18% for hot-rolled coil and 23% for busheling scrap.

I hypothesize that public price signals created by the futures markets improve steel buyers' ability to assess whether to buy from a given seller at the negotiated price or to negotiate further with other producers for a better price. Indeed, ample anecdotal evidence suggests that futures prices act as reference prices in negotiations between steel producers and their customers.[15]

The key prediction of this reference price channel is a decrease in the equilibrium price dispersion (Janssen, Pichler, and Weidenholzer, 2011; Duffie, Dworczak, and Zhu, 2017; Grennan and Swanson, 2020). A second prediction is that market shares become more sensitive to production costs, as buyers are better able to identify low-cost producers (Duffie, Dworczak, and Zhu, 2017). A third prediction is that sellers set lower markups, resulting in lower product prices (Janssen, Pichler, and Weidenholzer, 2011; Duffie, Dworczak, and Zhu, 2017). Customers can use the information contained in futures prices to decide whether to buy at a given price or to continue searching for a better offer. Sellers account for this and adjust their markups and prices downward in equilibrium. Thus, the availability of futures prices limits sellers' ability to exploit customers' lack of price information. Furthermore, the reallocation of market shares toward low-cost producers, induced by the availability of reference prices, lowers average production costs, which in turn further reduces prices.

[15]Figure A.2 shows that media discussions about reference prices in the steel industry increased with the development of steel futures. Internet Appendix C.4 presents selected media discussions on the impact of steel futures on price transparency.

3.1.2 Risk Management, Price Setting and Competition for Market Share

Futures markets may also impact the product market through a risk management channel. The introduction of futures can influence firms' risk management practices, which may in turn affect their behavior in the product market.

First note that the effect of centralized futures markets on firms' ability to manage steel price risk is theoretically ambiguous. On the one hand, centralized markets can improve hedging due to lower counterparty risk and higher liquidity compared to OTC contracts (Telser and Higinbotham, 1977; Telser, 1981). Supporting this view, Vuillemey (2020) finds that central clearing for coffee futures improved importers' hedging ability by solving a missing market problem for counterparty risk (Biais, Heider, and Hoerova, 2012) and reducing adverse selection (Bester, 1987).

On the other hand, Hirshleifer (1971) argues that revealing information can reduce risk-sharing opportunities in insurance markets. Therefore, the increased price information generated by the futures markets may make it harder for firms to share steel price risk (Marin and Rahi, 2000; Goldstein and Yang, 2022). Thus, the net effect on firms' risk management is an empirical question.

Changes in firms' risk management, in turn, may alter their behavior in the product market. Hedging stabilizes cash flows, enabling firms to avoid underinvestment due to insufficient internal funds in the presence of capital market imperfections (Froot, Scharfstein, and Stein, 1993). Empirically, improvements in hedging opportunities have been shown to increase investment in both tangible and intangible capital (Pérez-González and Yun, 2013; Gilje and Taillard, 2017; Brogaard, Dimitrova, and Eswar, 2019).

Furthermore, Chevalier and Scharfstein (1996) show that a shortfall of internal funds distorts price setting in markets where the customer base is sticky. In such *customer markets*, price setting involves an intertemporal trade-off and can be viewed as an investment decision. In the presence of customer switching costs, pricing low reduces short-term profits but increases market share, which can lead to higher long-term profits from repeat customers (Klemperer, 1987). With imperfect capital markets, a shortfall in cash flows distorts this trade-off: liquidity-constrained firms underinvest in market share by setting higher prices to boost short-term profits.

Empirically, liquidity-constrained firms have been shown to set higher prices (Chevalier and Scharfstein, 1996; Gilchrist et al., 2017), and customer markets are widespread in the U.S. economy, including commodity-producing industries (Foster, Haltiwanger, and Syverson, 2008, 2016; Hottman, Redding, and Weinstein, 2016).

Taken together, these considerations lead to the following predictions: If the arrival of the futures markets improves firms' hedging ability, stabilized cash flows enable firms to set lower prices in situations where insufficient internal funds would otherwise lead to underinvestment in market share and higher prices. As a result, average prices should decrease. Additionally, increased competition for market share should lead to a reallocation of market shares toward low-cost firms. Conversely, if the futures markets impair firms' hedging ability, the opposite effects are expected.

3.2 Effects on Producers

These product market effects have implications for firms selling the affected products. If the futures markets increase competition in the product market, this should reduce markups and thus lower firms' operating profits and valuations, all else equal.[16] However, the futures markets may also impact firms through channels

[16]Specifically, profits should decrease if lower markups are not fully offset by an increase in quantities sold. Valuations should decrease if reductions in the discount rate do not offset lower profits.

other than product market competition. Information contained in futures prices can enable producers to make better production decisions, potentially increasing their operating profit. Conversely, this information could harm producers by reducing their ability to exploit informational advantages in speculative trading and by diminishing risk-sharing opportunities (Goldstein and Yang, 2022).

Based on the above, futures markets may affect the product market through a reference price and a risk management channel. The availability of reference prices and improved risk management should lower product prices and increase competition for market share, harming firms that sell the affected products. Beyond these competitive effects, firms may benefit from better production decisions but may also face fewer opportunities for speculation and risk-sharing. Note that these channels are not mutually exclusive and can operate simultaneously.

In the empirical tests, I first examine whether the futures markets affect price dispersion (the key prediction of the reference price channel) and producers' risk management. Next, I test the predictions related to market share allocation and prices in the product market. Finally, I assess the net effect on producers' profits and valuations.

4 Empirical Strategy

4.1 Data

To examine how centralized futures markets impact the physical product market, I use four complementary data sources: product-level price data, public firms' accounting data, annual reports, and stock prices.

4.1.1 Product-level

I obtain proprietary data on reported prices for six different steel products sold to U.S. customers until December 2017. These products include hot-rolled coils, cold-rolled coils, standard plates, busheling scrap, heavy melting scrap, and shredded scrap. Data for hot-rolled and cold-rolled coils begins in the first week of 2007, for standard plates in the second week of 2008, and for scrap products in the second week of 2009. The data is collected by *SteelBenchmarker*, which was launched in 2006 to establish reliable price indices for settling steel futures contracts. Price indices are published on the second and fourth Wednesday of each month, with firms reporting prices over the five-day period preceding each publication date. Reported prices reflect the price provider's most recent actual transaction for delivery in two to six weeks (World Steel Dynamics, 2017). I obtain access to the full universe of prices submitted to *SteelBenchmarker*. This allows me to measure both the level of prices and their dispersion across reporting firms for a given product and publication date. For confidentiality reasons, *SteelBenchmarker* does not observe the identities of reporting firms, preventing me from linking price submissions back to specific firms.

4.1.2 Firm-level

To identify firms selling treated products, I use the product descriptions that firms are required to include in their annual reports (Hoberg and Phillips, 2016).[17] I begin with all firms headquartered in the U.S. and listed in the Compustat North America Fundamentals Quarterly file for 2003–2017. Next, I scrape firms' annual reports from the Securities and Exchange Commission for information on their products, commodity

[17]In principle, one could also study firms buying the treated products. However, steel is only one of many inputs for these firms, making it difficult to detect any effect of the futures markets. Additionally, while firms must report the products they sell, they are not required to report the specific products they use as inputs.

derivatives, and production technologies.

For the 2008 introduction of HRC futures, I classify firms as treated if they operate in NAICS industry 3311 (Iron and Steel Mills and Ferroalloy Manufacturing) and report selling hot-rolled coil in their annual reports prior to the start of HRC trading in October 2008. For the 2012 introduction of BUS futures, I classify firms as treated if they report operating a ferrous scrap business in their annual report before BUS trading began in September 2012. Next, I manually verify whether firms sell rather than buy the treated products. Finally, I restrict the sample to firms in metal-producing and recycling industries. Internet Appendix B provides details on the process of identifying treatment status, commodity derivatives, and production technologies from firms' annual reports, as well as on sample construction.

I use quarterly accounting data from Compustat to measure firm characteristics and daily stock prices from CRSP to study the stock market reaction to news increasing the likelihood of steel futures. All variables are winsorized at the 1st and 99th percentile. Variable definitions are provided in Table C.5.

4.2 Empirical Design

I implement a difference-in-differences (DiD) strategy, to identify the causal effect of centralized futures markets on the underlying product markets. This approach compares steel products with futures trading to similar steel products before and after the introduction of the futures markets.

In the early 2000s, several exchanges began publicly considering launching futures markets for various steel products. Figure A.3 shows that newspaper articles mentioning steel futures increased rapidly around 2003. This coincided with a general increase in the number of commodity futures approved by the Commodity Futures Trading Commission (CFTC). These patterns suggest that broader trends, such as lower costs of futures introductions due to electronic trading and increased volatility in commodity markets (e.g., Cheng and Xiong, 2014; Brogaard, Ringgenberg, and Sovich, 2019), were driving the interest in steel futures.

At the time of developing U.S. steel futures contracts, NYMEX and CME were widely held, publicly listed for-profit companies. Therefore, potential externalities from the creation of the futures markets on product markets were unlikely a major driver in the exchanges' decision process. In deciding which steel product to use as an underlying in futures contracts, exchanges face a trade-off between minimizing basis risk and maximizing liquidity. Offering a futures contract for each steel product in each regional market would minimize basis risk. However, it could lower the liquidity of each contract, as total steel-related speculation and hedging demand would be split across different futures contracts.

In the product-level tests, I rely on prices reported to *SteelBenchmarker*, which was launched to establish price indices for settling steel futures contracts. This data includes prices for treated products (hot-rolled coils, busheling scrap) and control products (cold-rolled coils, plates, shredded scrap, heavy melting scrap). Initially, these products were all considered candidates for futures trading in the U.S. Indeed, NYMEX was developing a cold-rolled coil (CRC) futures contract for the U.S. but discontinued the development after its merger with CME Group in 2008. In November 2019, NYMEX introduced a contract for U.S. shredded scrap (SHR).[18]

The fact that NYMEX initially developed CRC futures before the CME merger and later introduced SHR futures indicates that there is no fundamental difference between treated and control products in terms of suitability for futures trading. Supporting this, price volatility—a key requirement for viable futures contracts (Carlton, 1984)—increased similarly across all steel products in the early to mid-2000s. Notably,

[18] I obtain price data until December 2017. Therefore, I cannot study the NYMEX shredded scrap futures introduction in 2019.

treated products did not show higher levels of price volatility before the introduction of NYMEX steel futures, nor did they experience a more pronounced increase in volatility compared to control products, as illustrated in Figure A.4 and Table A.2.[19]

In the DiD estimation, I compare hot-rolled coils and busheling scrap to other steel products tracked by *SteelBenchmarker* before and after the establishment of their respective futures markets. This comparison controls for common shocks to all steel products. Note that the key identifying assumption in the DiD analysis is not the random assignment of centralized futures trading, but rather that treated and control steel products would have followed similar trends in the absence of the futures market.

Three key facts support this parallel trends assumption. First, treated and control products are comparable in terms of cyclicality ex-ante, mitigating concerns about differential business cycle effects. Table A.3 shows that while overall steel prices correlate positively with U.S. GDP and major steel-consuming sector output (automotive, construction, machinery, appliances), treated and control product prices do not differ in their comovement with aggregate economic conditions and major steel-consuming sectors before the arrival of the NYMEX futures markets.

Second, outcomes for treated and control products, as well as for firms selling these products, exhibit similar trends before the introduction of the NYMEX futures markets. Third, parallel trends continue to hold for non-U.S. firms after the arrival of the U.S.-targeted futures markets: outcomes for firms selling treated products outside the U.S. evolve similarly to those of control producers after the introduction of the

[19]Since the *SteelBenchmarker* data is only available from 2007 onward, I use producer price indices (PPIs) for different steel product groups to document trends in steel price volatility before the arrival of the first NYMEX steel futures contracts in Figure A.4 and Table A.2. Using the *SteelBenchmarker* data, I also do not find significant differences in the level of price volatility for treated and control products before the respective introduction.

NYMEX futures markets. This mitigates concerns that other events coinciding with the futures markets' arrival affected treated and control products differently.

A potential concern in DiD settings is spillover effects. If the NYMEX futures markets affect information or risk management for both treated and—to a lesser extent—control products, spillovers to related products should follow the same direction as the effects on treated products. Such spillover effects could bias the estimates toward zero, meaning the results can be considered a lower bound.

4.3 Specification

This section outlines the specification used to estimate the effect on product market price dispersion. I present adapted specifications to estimate the effects on firms selling the treated products right before discussing the corresponding results.

For each publication date, I measure price dispersion across different reporting firms for a given product. *SteelBenchmarker* collects and releases price data twice per month. The price submission data begins in the first week of January 2007, providing 40 releases before the trading start of HRC futures. Consequently, I select a window of 40 publication dates surrounding the futures introductions.

To conduct the DiD analysis, I construct a product-publication date panel from $t = -40$ to $t = 40$ for each futures introduction (HRC, BUS), where $t = -1$ denotes the last publication date before the start of futures trading. Given that price data for scrap products are only available from 2009 onward, I focus solely on hot-rolled coils, cold-rolled coils and standard plates in the HRC panel. The HRC panel spans January 2007–June 2010, while the BUS panel includes January 2011–May 2014. Finally, I stack the observations from both panels and estimate the following DiD model:[20]

$$\textit{Price Dispersion}_{k,p,t} \quad = \quad \beta.\textit{Post}.\textit{Futures}_{product,k,p} + \alpha_{k,p} + \alpha_{k,t} + \varepsilon_{k,p,t}. \tag{1}$$

Futures introductions (HRC, BUS) are indexed by k, products by p, and publication dates by t. I measure *Price Dispersion*$_{k,p,t}$ as either the standard deviation (*SD(Price)*) or the coefficient of variation (*CV(Price)*) across different reporting firms for a given product p and publication date t. The dummy variable *Futures*$_{product}$ equals one for hot-rolled coils around the HRC introduction and for busheling scrap around the BUS introduction. The dummy variable *Post* equals one after HRC futures began trading on October 20th, 2008, for the HRC introduction and after BUS futures began trading on September 14th, 2012, for the BUS introduction. $\alpha_{k,p}$ and $\alpha_{k,t}$ represent futures introduction-specific product and publication date fixed effects. Standard errors are clustered by publication date.[21] The coefficient of interest β measures the change in price dispersion for treated relative to control steel products after the introduction of centralized futures.

4.4 Summary Statistics

Table 1 presents summary statistics. Panel A shows the treatment indicator and outcomes for the product-level panel: 32% of observations are classified as treated, and the average price per ton across all products during the sample period is 710 USD. The average dispersion of prices across different price providers for a given product and publication date is 126 USD, or 19% relative to the respective average price. This

[20]Results are robust to using the entire length of the available data, extending the post period until December 2017. Results are also robust to excluding HRC products and firms selling HRC from the second panel around the BUS introduction.

[21]Results are robust to two-way clustering by product and date. Table A.4 shows the standard errors of the baseline results using alternative clustering choices. Results are also robust to two-way clustered bootstrapping, using wild bootstrap with Webb weights (Cameron, Gelbach, and Miller, 2008; Cameron and Miller, 2015; Webb, 2023) to address the issue raised by Moulton (1990).

substantial price dispersion is similar in magnitude to that documented in other business-to-business settings where prices are negotiated bilaterally (Grennan and Swanson, 2020).

[Table 1 around here.]

Panel B presents the treatment indicator and outcomes for the firm-level panel: 4% of observations are classified as treated, and 26% of firms discuss using commodity derivatives in their annual reports in a given year (*Hedge (1/0)*).[22] The average market share within firms' 4-digit NAICS industry is 8.5%, and the average operating profit, scaled by beginning-of-quarter total assets, is 2.8%. Panel C shows the average pre-treatment values of the baseline firm-level control variables: The average firm has total assets worth 2.4 billion USD, is 38 years old, and experiences 2.2% sales growth. Panel D shows that the average cumulative abnormal return around news events related to futures introductions is about -1%.

5 Results

In this section, I first examine the effect of centralized futures markets on price dispersion in the physical product market, before studying firms' hedging activity. Next, I document the effect of the futures markets on market share allocation and price levels in the product market. Finally, I study the impact on producers' profits and valuations.

[22]The literature documents similar magnitudes: 16% of firms use commodity derivatives (Almeida, Hankins, and Williams, 2017), 27%-36% use interest rate derivatives (Campello et al., 2011; Chernenko and Faulkender, 2011), 14%-55% use foreign exchange derivatives (Campello et al., 2011; Hoberg and Moon, 2017; Brogaard, Dimitrova, and Eswar, 2019), and 25% of utilities use weather derivatives (Pérez-González and Yun, 2013).

5.1 Price Dispersion in the Physical Product Market

If the public price signals generated by the futures markets act as reference prices in negotiations between sellers and buyers of physical steel, price dispersion in the product market should decrease for treated products after the introduction of the futures market (Janssen, Pichler, and Weidenholzer, 2011; Duffie, Dworczak, and Zhu, 2017; Grennan and Swanson, 2020). Table 2 confirms this prediction. Column (1) of Panel A shows that the standard deviation of prices across different reporting firms decreases by about 39 USD per ton for treated relative to control products after futures commence trading. Column (1) of Panel B shows that the coefficient of variation decreases by 6 percentage points.

To mitigate concerns that other factors driving steel prices confound the effects of steel futures, Columns (2) to (5) add controls for domestic steel demand and supply, as well as international trade. Column (2) includes quarterly U.S. GDP growth and output growth of key steel-consuming sectors (automotive, construction, machinery, appliances) to capture domestic steel demand. Column (3) includes annual growth in U.S. steel production quantities and capacity utilization to capture domestic steel supply. Column (4) adds annual growth in global steel production quantities and steel imports into the U.S. to capture international trade. These time-varying proxies for changes in aggregate steel demand and supply are interacted with the treated product indicator, $Futures_{product}$, to capture differential effects on treated and control products. Column (5) adds all controls simultaneously. Notably, the coefficient estimates remain significant at the 1% level throughout, and magnitudes are remarkably stable across specifications.

[Table 2 around here.]

To assess the validity of the empirical design and study the dynamics of the effect, I replace the post dummy in Equation 1 with dummies for each time period, following the common practice of choosing

$t = -1$ as reference period.[23] Figure 2 plots the coefficients. Importantly, treated and control product price dispersion exhibit parallel trends before the introduction of the futures markets, supporting a causal effect of the futures markets on product market price dispersion. The coefficients show no evidence of anticipation effects, as the impact appears only after the start of futures trading. Finally, the effect persists until the end of the sample period, suggesting a permanent shift due to the arrival of the futures markets rather than the influence of transitory confounding events.

[Figure 2 around here.]

5.2 Risk Management

To explore the risk management mechanism through which the futures markets may affect the product market, I compare firms selling hot-rolled coil and ferrous scrap to other metal producing and recycling firms before and after the introduction of the futures contracts.

Figure A.5 shows that open interest in the NYMEX contracts begins to build right after the start of futures trading. Next, I assess whether this build-up in open interest translates into increased hedging of commodity price risk for firms selling the treated products. Following previous work (e.g., Pérez-González and Yun, 2013; Almeida, Hankins, and Williams, 2017), I construct a dummy variable equal to one if firms discuss hedging with commodity derivatives in their annual reports.

For each futures introduction (HRC, BUS), I distinguish between a pre-futures period (years $y = -4$ to $y = -1$), and a post-futures period (years $y = 0$ to $y = 4$). I create a firm-year panel from $y = -4$ to

[23] Choosing $t = -1$ as the base level makes diverging trends easily recognizable but comes with the cost of reduced statistical power, as selecting only one point in time as the base level inflates the standard errors. Table A.5 presents dynamics where pre-period coefficients are constrained to sum to zero (Miller, 2023).

$y = 4$, where $y = -1$ denotes the last year before the start of futures trading. I then stack the observations from the two panels to estimate the following DiD model:

$$\textit{Hedge (1/0)}_{k,i,y} = \beta.Post.Futures_{firm,k,i} + \sum_{\tau=-4}^{4} \left(\theta'_{\tau}.X_{k,i}\right) \mathbb{1}\left\{y = \tau\right\} + \alpha_{k,i} + \alpha_{k,y} + \alpha_{k,j,y} + \varepsilon_{k,i,y}. \quad (2)$$

Futures introductions (HRC, BUS) are indexed by k, firms by i, years by y, and 3-digit NAICS industries by j. *Hedge (1/0)*$_{k,i,y}$ equals one if firm i mentions using commodity derivatives in its annual report in year y, *Futures*$_{firm}$ equals one for firms selling HRC (ferrous scrap) for the HRC (BUS) introduction, and *Post* equals one starting in 2008 for the HRC introduction and in 2012 for the BUS introduction.

I also introduce a vector of control variables $X_{k,i}$, measured in the last quarter before the introduction and interacted with year fixed effects. I include controls for firm size, age, and sales growth to mitigate concerns that differential trends in these dimensions confound the estimates.[24] By using pre-treatment values interacted with time fixed effects, I avoid concerns about endogenous controls: contemporaneous values of the control variables (i.e., as of year y) are endogenous and thus considered "bad controls" (Angrist and Pischke, 2009). $\alpha_{k,i}$, $\alpha_{k,y}$, and $\alpha_{k,j,y}$ are futures introduction-specific firm, year, and industry-year fixed effects. Standard errors are clustered by firm.[25] The coefficient of interest β measures the change in the propensity to use commodity derivatives for treated relative to control firms after the introduction of centralized futures.

Table 3 shows that treated firms are more likely to discuss the use of commodity derivatives in their annual reports compared to control firms after the start of futures trading. This provides evidence that the

[24] Table A.6 shows that treated and control firms are similar in terms of age and sales growth. However, treated firms are larger on average, highlighting the importance of controlling for these differences.

[25] I cluster standard errors by firm since treatment status is defined based on firms' product descriptions. Results are robust to clustering standard errors by groups of firms based on product similarity in annual reports instead, as shown in Table A.4.

futures markets led firms selling treated products to rely more on commodity derivatives to manage price risk.

[Table 3 around here.]

Figure 3 demonstrates that treated and control firms exhibit parallel trends in commodity hedging before the introduction of the futures markets, with no evidence of anticipation effects.

[Figure 3 around here.]

These findings suggest that the centralized futures markets prompt firms to increase their hedging of steel price risk. Table A.7 provides further evidence supporting this notion: After the arrival of the futures markets, treated firms' profits become less correlated with steel prices relative to control firms. Thus, the net effect of the centralized futures markets is that treated firms isolate their profits more from steel price risk in the context of the NYMEX steel futures.[26]

5.3 Cost Sensitivity of Market Shares

In the previous sections, I document that the futures markets decrease price dispersion in the product market. This finding is consistent with the futures markets providing reference prices for negotiations between producers and customers. With reference prices available, buyers can more effectively identify low-cost sellers, thereby increasing market share sensitivity to cost (Duffie, Dworczak, and Zhu, 2017). Additionally,

[26]Under SFAS 133, changes in the hedged item are offset against changes in the corresponding derivatives used effectively for hedging purposes. For output price hedging, this reduces the correlation between output prices and operating profits. See Ranasinghe, Sivaramakrishnan, and Yi (2022) for a discussion of hedge accounting for output price risk.

I find that producers increase their hedging activity and more effectively isolate their profits from steel price risk. This improved hedging could mitigate underinvestment in market share due to insufficient internal funds (Froot, Scharfstein, and Stein, 1993; Chevalier and Scharfstein, 1996), thereby enhancing low-cost producers' ability to capture market share by lowering prices.

To test whether market shares become more sensitive to production costs, I leverage the distinction between two methods of producing raw steel: basic oxygen furnaces (BOF) using iron ore and electric arc furnaces (EAF) using steel scrap. The cost advantage of these technologies varies with the prices of iron ore and scrap. Since these technologies are relevant only for raw steel production and do not apply to firms selling ferrous scrap, I restrict the sample to the HRC introduction. I identify steel producers operating EAFs from firms' annual reports before the HRC introduction.[27] For each year-quarter, I calculate the ratio of iron ore to scrap prices, creating a time-varying measure of the relative cost advantage between the two production methods.[28]

I compute firms' market share within their 4-digit NAICS industry for each year-quarter. To align with the time frame of the product-level tests, I use data from 7 quarters before and after the HRC futures introduction in Q4 2008, covering Q1 2007 to Q3 2010. I then estimate the following DiD model:

$$\textit{Market Share}_{i,q} = \beta.\textit{Post}.\textit{Futures}_{firm,i}.\textit{EAF}_i.\textit{Iron/Scrap}_q + \alpha_i + \alpha_q + \alpha_{j,q} + \varepsilon_{i,j,q}, \tag{3}$$

where i indexes firms, q indexes year-quarters, and j indexes industries at the 3-digit NAICS level. *Futures*$_{firm}$ equals one for HRC producers, *Post* equals one starting in Q4 2008, and *EAF* equals one for producers using EAFs. *Iron/Scrap* represents the ratio of iron ore prices to scrap prices. α_i are firm fixed

[27] Internet Appendix B provides the details.

[28] I use the PPI for Iron Ore (WPS1011) and Iron and Steel Scrap (WPS1012). Figure A.6 plots the evolution over time.

effects, α_q are year-quarter fixed effects, and $\alpha_{j,q}$ are industry-year-quarter fixed effects. The regressions include all interactions of *Post*, *Futures*$_{firm}$, *EAF*, and *Iron/Scrap*. The coefficient of interest β measures the change in market share sensitivity to iron ore relative to scrap prices for treated versus control EAF producers after the introduction of the futures market. When iron ore prices rise relative to scrap prices, EAF producers benefit from lower production costs compared to BOF producers.

Table 4 shows that when iron ore prices increase by 10% relative to scrap prices, the market share of treated EAF producers increases by 0.5 to 0.8 percentage points more after the arrival of the futures market compared to control EAF producers. These results are robust to controlling for 3-digit NAICS industry-year-quarter fixed effects and initial firm characteristics interacted with year-quarter fixed effects. This increased responsiveness of market shares to costs is consistent with the futures market intensifying competition for market share in the product market.

[Table 4 around here.]

5.4 Price Level in the Physical Product Market

Next, I test whether centralized futures markets reduce prices in the physical product market. Increased competition should lead to lower prices by reducing markups and reallocating market share toward low-cost producers. Using the natural logarithm of the price per ton as the outcome variable in Equation 1, Table 5 shows that product market prices decrease by 3 to 4% for treated products relative to control products following the introduction of futures contracts. These findings remain statistically significant at the 1% level and exhibit stable magnitudes when controlling for factors affecting steel demand, supply, and trade.

[Table 5 around here.]

Figure 4 plots the dynamics of the effect. Notably, treated and control product prices are on parallel trends before the futures markets introduction. The effect becomes evident only after futures start trading and persists until the end of the sample period.[29] Taken together, these results are consistent with increased competition leading to lower markups and a reallocation of market share toward low-cost producers, resulting in lower prices.

[Figure 4 around here.]

5.5 Producer Operating Profits

The previous section shows that futures markets decrease physical product market prices. Next, I estimate the effect on the operating profits of firms selling the treated products. Increased competition in the product market should lead to lower operating profits for producing firms, all else being equal. However, centralized futures markets may enable producers to make better production decisions, which could increase their operating profits and potentially offset the competition effect.

I construct a firm-year-quarter panel covering quarters $q = -7$ to $q = 7$ for each futures introduction (HRC, BUS), where $q = -1$ denotes the last quarter before the start of futures trading. I then stack the observations from both panels and estimate specifications similar to Equation 2. The outcome variable $\textit{Profit}_{k,i,q}$ is defined as operating profit (Compustat item oibdpq) scaled by beginning-of-quarter total assets (Compustat item atq).

Table 6 presents the results. In Column (1), I regress *Profit* on the interaction between $\textit{Futures}_{firm}$ and

[29]Note that the standard errors in Figure 4 are large due to the choice of using a single period ($t = -1$) as the base level. Estimating the coefficients relative to multiple pre-periods, as proposed by Miller (2023), results in significantly smaller standard errors, shown in Table A.5.

Post, while controlling for firm and industry-year-quarter fixed effects specific to each futures introduction ($\alpha_{k,i}$ and $\alpha_{k,j,q}$). Column (2) includes the baseline pre-treatment firm controls (size, age, sales growth) interacted with year-quarter dummies.

[Table 6 around here.]

The estimated coefficients on *Post.Futures*$_{firm}$ show that operating profits for treated producers decrease by 1.6 to 1.9 percentage points relative to control producers, statistically significant at the 1% level. These results indicate that the competition effect outweighs the impact of improved production decisions in the context of the NYMEX steel futures.

In Columns (3) to (9), I augment the firm-level data with aggregate and sectoral data to control for various potential confounders. The estimates remain significant at the 1% level throughout and are remarkably stable across specifications. I discuss these tests in detail in Section 6. In terms of economic magnitude, the profit results align with the price results presented in Table 5. Given the sample mean of sales/assets of 0.4, a 4% decline in prices should lead to a decrease in operating profit/assets by $0.4 \times 4 = 1.6$ percentage points, ceteris paribus.

Figure 5 illustrates the dynamics of the effect. Importantly, profits of treated and control firms follow parallel trends before the introduction of the futures markets, supporting a causal effect of the futures markets on firms' profitability in the product market. The impact emerges only after the start of futures trading, indicating no anticipation effects. Furthermore, the effect persists until the end of the sample period, consistent with a permanent rather than transitory change. Overall, the results for producers' operating profits align with an increase in competition in the product market.

[Figure 5 around here.]

5.6 Producer Stock Market Valuations

The results above show that the centralized futures markets reduce producers' operating profits. I now turn to evaluating the impact on stock market valuations. Increased competition in the product market should lead to lower valuations for producers.

To examine the effects on the valuations of firms selling treated products, I analyze stock market reactions to significant news events that increased the likelihood of HRC and BUS futures contracts. The creation of futures contracts for steel products was a lengthy process, marked by significant uncertainty regarding whether and when futures contracts would be introduced, and which products would be covered.

I consider five significant events for the 2008 HRC futures introduction. The first is a contract signed between NYMEX and World Steel Dynamics to use *SteelBenchmarker* prices for settling HRC futures. However, this contract did not materialize because NYMEX was acquired by CME Group before implementation.[30] Prior to the merger, CME had instructed the CRU Group, a commodity research firm, to develop a price index to settle HRC futures. Following the merger, NYMEX's initial plans were abandoned, and the newly-formed CME/NYMEX entity announced the launch of HRC futures in fall 2008, settling against the price index developed by CRU. For the 2012 BUS futures introduction, key events include the signing of a licensing agreement between CME/NYMEX and American Metal Market (AMM) for the AMM ferrous scrap index, and the official announcement that U.S. Midwest busheling scrap futures would be traded on the exchange.[31]

I estimate cumulative abnormal returns (CAR) for treated and control producers around these events

[30] NYMEX accepted the CME Group's offer in March 2008, and the merger was completed in August 2008.

[31] The AMM ferrous scrap index was launched in June 2012, coinciding with the signing of the licensing agreement.

using the market model, the CAPM, the Fama-French three-factor model (Fama and French, 1993), and the Carhart four-factor model (Carhart, 1997). I then estimate the following OLS regression:

$$CAR_{i,e} \quad = \quad \beta.\textit{Futures}_{firm,i,e} + \alpha_e + \alpha_i + \varepsilon_{i,e}, \tag{4}$$

where i indexes firms and e indexes events. *CAR* is the cumulative abnormal return on firm i's stock during the five-day window surrounding the event. $\textit{Futures}_{firm}$ equals one for firms selling HRC (ferrous scrap) on events related to the HRC (BUS) futures introduction.[32] Internet Appendix C.3 lists the events with the corresponding futures introduction (HRC, BUS) and event dates. Standard errors are clustered by firm.

Table 7 presents the results. *CAR* is measured as the firm's excess stock return relative to the CRSP value-weighted portfolio in Column (1), the CAPM in Column (2), the Fama-French three-factor model in Column (3), and the Carhart four-factor model in Column (4). The estimated coefficients on $\textit{Futures}_{firm}$ are negative and statistically significant at the 1% level across all four columns. Firms selling treated products experience a 4% to 5% drop in stock market valuations during the five-day window surrounding news that increases the likelihood of a centralized futures market, compared to the control group.[33]

[Table 7 around here.]

[32]One concern is that news about the BUS introduction might increase stock prices of firms using scrap as an input, potentially confounding the effect of BUS futures on scrap-selling firms. To address this issue, I exclude firms operating electric arc furnaces (which primarily use scrap) from the BUS news events.

[33]The findings are robust to using alternative event windows, e.g., from trading day $d-2$ to $d+3$ or from $d-3$ to $d+3$, and are not driven by any particular event: Removing any event date from the sample yields similar results as shown in Figure A.7. Since I consider 5 HRC events and 2 BUS events, the total decrease in valuations would amount to 20–25% for the HRC introduction and 8–10% for the BUS introduction. However, information both increasing and decreasing the likelihood of a futures contract likely arrived also outside the event windows. Therefore, these magnitudes for the total effect should be taken with some caution.

Figure 6 presents the dynamics of the effect during the 21-day window surrounding the events. While treated and control firms exhibit similar abnormal returns prior to the event date, treated firms' abnormal returns begin to decrease relative to control firms around the news release. The effect appears to be fully priced in six days after the event. Taken together, the results are consistent with investors anticipating the profit effect documented in Table 6, leading to lower stock market valuations for producing firms.[34]

[Figure 6 around here.]

These valuation results are consistent with increased competition. They also align with the idea that information revealed by futures prices diminishes speculation and risk-sharing opportunities for producers. However, such a loss of trading opportunities should be confined to producers engaged in commodity derivatives trading (Goldstein and Yang, 2022). In contrast, lower profits resulting from higher competition in the product market should negatively impact producers regardless of their involvement in commodity trading.

In Table A.10, I split the sample of producers based on two proxies for ex-ante commodity derivative usage: i) an indicator for producers discussing commodity derivatives in their annual reports (Columns (1) and (2)), and ii) an indicator for producers with an estimated propensity to discuss commodity derivatives above the median, based on observable firm characteristics (Columns (3) and (4)). These proxies are measured over the years 2004-2007. The first proxy relies on actual disclosure of commodity derivatives, while the second captures firms with characteristics (size, age, sales growth, tangibility, leverage, industry) typical of those that disclose commodity derivatives.

I find similar valuation results in the subsample of producers unlikely to have used commodity deriva-

[34] A concern here is whether investors were able to anticipate and price in the profit effect. However, as shown in Figure A.3, media attention to steel futures was high around the introductions, and the futures were expected to increase price transparency.

tives before the arrival of steel futures. Since the valuation results in this subsample are unlikely to be driven by lost trading opportunities, they provide additional evidence that futures markets increase product market competition, thereby depressing producers' valuations.

The combined evidence in Tables 4, 5, 6, and 7 shows that the centralized futures markets increase the market share of low-cost firms while reducing product prices, sellers' profits and stock market valuations. This is consistent with an increase in competition in the product market that, while anticipated by stock markets, producers were unable to escape.

6 Discussion

6.1 Other Events

A legitimate concern is that other events confound the estimation of the futures markets' effects. In this section, I discuss a series of tests to address potentially confounding events. Most notably, negative demand shocks during the Great Recession may have affected treated and control products differently. A stronger inward shift of the demand curve during downturns could lead to lower prices for treated products and lower profits for firms selling these products.

Below, I present four sets of results to mitigate this concern. First, I find no evidence that production quantities decrease for treated products relative to control products. Second, treated firms' sales are not more sensitive to economic fluctuations before the arrival of the futures markets. Additionally, controlling for firms' sensitivity to economic conditions does not explain the lower profits for treated firms. Third, the results are robust to excluding the 2008 HRC introduction and the crisis period altogether. Fourth, the arrival of the U.S. futures markets has no effect on firms selling treated products in markets remote from the U.S.

6.1.1 Production Quantities

The first test to address negative demand shocks studies how production quantities of treated and control products evolve around the arrival of the futures markets. If the demand curve for treated products shifts inward more strongly during recessions, production quantities should decrease relative to control products.

I obtain data on product-level quantities from the U.S. Geological Survey and use similar specifications as in the price tests. This data covers U.S. steel production aggregated by product on a yearly basis. While aggregating data across all U.S. plants and over a full year smooths out cross-sectional and temporal fluctuations, it results in a smaller sample size and limited statistical power. Therefore, the estimates should be interpreted with some caution. As shown in Table A.8, production quantities of treated products do not decrease relative to control products. The point estimates are positive rather than negative and are statistically insignificant, inconsistent with a stronger inward shift in demand for treated products.

6.1.2 Controlling for Potential Confounders of Firm Profits

As a second test, I examine whether the reduced profits for treated firms can be attributed to differences in their sensitivity to economic conditions. I estimate firms' sales beta with respect to GDP and key steel-consuming industries (i.e., automotive, construction, machinery, and appliances).[35] As shown in Table A.6, treated and control firms are comparable in terms of exposure to overall economic activity and these steel-consuming sectors ex-ante. Furthermore, controlling for firms' ex-ante exposure—interacted with year-quarter fixed effects—in the profit tests yields similar point estimates, as shown in Column (3) of Table 6.

[35] I estimate these betas by regressing firms' annual sales growth separately on GDP growth and on sales growth in the various industries in the 20 years before the respective introduction. Table A.11 presents summary statistics for additional control variables.

This indicates that the profit results are not driven by differential exposure to aggregate activity or specific steel-consuming sectors.

Additionally, I control for other potential confounders of the firm profit results, such as changes in input costs and import competition. Since raw steel production relies on either iron ore or scrap, variations in these input prices could impact profits. To address this, I include firms' sensitivity to iron ore versus scrap prices, interacted with year-quarter fixed effects, in the controls.[36] As shown in Table A.6, treated and control firms have comparable exposure to these input prices ex-ante. I further include a dummy for EAF producers (who primarily use scrap), interacted with year-quarter fixed effects, and interactions of the treatment indicator with the iron ore-to-scrap price ratio and the log of iron ore prices. The results in Column (4) of Table 6 remain robust to these controls, indicating that differential exposure to input prices does not drive the results.[37]

Regarding import competition, particularly from the largest steel producing countries—China, India, and Japan—I first test whether import competition increased for treated products and industries relative to control groups around the time of the futures introductions. The import data is aggregated at the product or industry level on a yearly basis, which smooths out fluctuations across importers and time but results in fewer observations and limited statistical power. Consequently, the estimates should be interpreted with some caution. As shown in Table A.12, there is no evidence of increased import competition for treated products

[36]I estimate firms' profit and cost-of-goods-sold (COGS) beta by regressing annual profits and COGS growth on changes in the iron ore-to-scrap price ratio over the 20 years prior to each introduction. Results are similar when controlling for iron ore and scrap prices separately.

[37]Further, unreported robustness tests show that COGS (scaled by beginning-of-quarter total assets) do not increase more for treated relative to control firms after the introduction of futures. The point estimates are not statistically significant and negative.

and industries after the introduction of steel futures. The point estimates are negative rather than positive and statistically insignificant, inconsistent with an increase in import competition for treated products and industries. Additionally, Column (5) of Table 6 includes interactions of industry-level import penetration with the treatment indicator as a control. The results remain robust, indicating that import competition does not explain the profit differences.[38]

Furthermore, the profit results remain robust to controlling for the share of sales in the firms' main industry and the share of sales outside the U.S., as shown in Column (6). This alleviates concerns about firms operating in multiple industries and countries.[39] The results are also robust to excluding firms involved in significant acquisitions around the futures introductions, shown in Column (7).[40] Finally, as shown in Table A.13, the hedging and market share results are also robust to controlling for the list of potential confounders discussed above.

6.1.3 Estimating Effects for HRC and BUS Futures Separately

Concerns about confounding events are particularly acute for the HRC introduction in October 2008, which may be confounded by the financial crisis and the housing market bust. Additionally, commodity prices experienced a boom-bust cycle in 2008: Steel and iron prices, along with many other commodities, rose sharply in the first half of 2008, then declined through the second half of the year until April 2009, before

[38] I set import penetration to 0 for non-manufacturing industries (NAICS 423), following Acemoglu et al. (2016).

[39] Excluding firms with more than 10% of their sales outside their main industry or outside the U.S. yields similar results.

[40] I exclude observations where acquisitions exceed 5% of assets, following Ottonello and Winberry (2020). Alternatively, excluding firms with comparability status (compst) of AA, AB, AF, AR, AS, CA, CB, or CC during the years 2007, 2008, 2009, 2011, 2012, or 2013 produces similar results.

recovering to exceed pre-crisis levels in January 2010. To address these potential confounders, I estimate the regressions separately for each futures introduction.[41] The results, shown in Table 8, remain robust when focusing only on the BUS introduction—spanning Q4 2010 to Q2 2014—thus excluding the financial crisis, housing bust, and commodity boom-bust period from the sample.[42]

6.1.4 Placebo Tests

Finally, I construct a sample of non-U.S. firms for placebo tests.[43] Since the steel market is geographically segmented and the NYMEX futures target the U.S. market, their effects should be confined to U.S. firms. In contrast, if treated products are differentially affected by changes in overall economic conditions around the futures introductions—for instance, because their technical properties lead to greater use in more cyclical sectors—these differential effects should also be observable in other regions with similar economic conditions.

To test these competing stories, I use a sample of publicly listed non-U.S. firms from Compustat Global and obtain their annual reports from Refinitiv. I exclude firms operating in countries where steel futures were introduced during the sample period.[44] Importantly, the resulting sample of countries experienced economic

[41]Note that the test on market shares in Table 4 is only feasible for the HRC introduction since the two production technologies (EAF and BOF) are used for raw steel production and do not apply to ferrous scrap selling firms, as discussed in section 5.3.

[42]The event study results in Table 7 are robust to excluding any one event, as discussed in section 5.6 and shown in Figure A.7. Table A.14 further shows that the results remain robust when excluding event windows with below-median market returns, addressing concerns that negative news about overall economic conditions could confound the effects.

[43]The *Steelbenchmarker* price submission data covers only the U.S. and thus does not permit similar placebo tests for the price level and dispersion results.

[44]Specifically, I exclude firms headquartered in the U.S., China, India, South Korea, Turkey, the UAE, and the Black Sea region

conditions similar to those in the U.S. during the sample period, as shown in Figure A.8.

I gather data on firms' products, commodity derivative usage, and production technologies from their annual reports, assigning firms to treatment and control groups using the same methodology as for U.S. firms. I then conduct placebo tests for all firm-level outcomes with specifications similar to the main tests.[45] The findings show no significant changes in commodity hedging, market share allocation, or profitability for treated versus control producers in the non-U.S. sample around the introduction of the NYMEX steel futures. Thus, despite exposure to similar economic conditions, the outcomes for treated producers do not differ from those for control producers in the non-U.S. sample. Additionally, treated firms' stock prices do not react differently to news about the NYMEX futures compared to control firms. These placebo tests mitigate concerns that other events coinciding with the introduction of NYMEX steel futures might have differentially affected treated and control producers. Detailed results are presented in Table 9 and in Figures A.9 to A.11.[46]

[Table 9 around here.]

(Bulgaria, Georgia, Romania, Russia, Ukraine). Additionally, I exclude firms with sales to these countries exceeding 1% of their total sales, based on data from FactSet GeoRev. Results are not sensitive to this 1% threshold. Firms in Canada and Mexico are also excluded to address potential spillovers within the NAFTA region.

[45] I add headquarter country fixed effects to account for country heterogeneity; results are similar without these fixed effects.

[46] In an alternative placebo test within the U.S. firm sample, I exclude firms selling the treated products (HRC, BUS) and assign placebo treatment status to firms selling products used as controls in the product-level tests (cold rolled coils, plates, heavy melting scrap, shredded scrap). Panel A of Table A.15 shows that placebo and treated firms are similar in their exposure to economic conditions and key steel-consuming sectors. Panel B demonstrates that placebo treatment does not correlate with firms' hedging activities, market share, profitability, or stock market returns around the arrival of NYMEX steel futures.

6.2 External Validity

The empirical results in this paper show that the arrival of centralized futures markets for steel products reduces price dispersion—the key prediction of the reference price channel—and increases firms' hedging activity. Additionally, the futures markets heighten the sensitivity of market share to cost and lower prices, profits, and valuations of firms selling the treated products, consistent with increased competition in the underlying product markets. An open question is the generalizability of these results to other markets. The main changes brought about by steel futures were increased price transparency and central clearing. Given that other modern futures contracts often share these features, they might similarly impact their underlying markets.

A key aspect of both the reference price and the risk management channels is product market frictions. In markets where customers can obtain final price quotes at no cost from many sellers, price dispersion should be low, and futures markets are unlikely to enhance price transparency. Therefore, the degree of price dispersion in the underlying product market indicates whether futures markets have the potential to improve price transparency. For the risk management channel to operate, financial constraints must prevent firms from lowering prices to gain market share in settings with a sticky customer base (i.e., customer markets). Notably, business-to-business markets often lack price transparency (Grennan and Swanson, 2020), and customer markets are widespread in the U.S. economy, including commodity-producing industries (Foster et al., 2008; 2016; Hottman et al., 2016). Consequently, futures markets could enhance competition in a variety of markets where futures trading is feasible.

The extensive use of futures prices as benchmarks in commodity markets suggests that futures markets indeed play such a role across various commodities. According to the World Bank, many major commodity markets rely on futures prices as benchmarks, providing price transparency for underlying physical products and enabling industry participants to manage risk effectively (Baffes and Nagle, 2022). For instance, the introduction of NYMEX futures for West Texas Intermediate (WTI) in 1983 enhanced price transparency by establishing WTI as a price benchmark for the North American oil market and improved industry participants' ability to manage price risk, according to CME Group (2023). Today, NYMEX WTI futures prices are widely used as a contracting benchmark between sellers and buyers of physical oil (Gilje et al., 2023). Similarly, London Metal Exchange (LME) futures serve as reference prices in physical contract negotiations for a range of industrial metals, including aluminum, copper, lead, nickel, tin, and zinc, and enable industry participants to manage price risk (LME, 2023, 2024). These examples underscore the potential for futures markets to enhance price transparency and risk management across various industries, suggesting broader applicability of the findings from this study.

7 Conclusion

This paper investigates the impact of centralizing derivative markets on the underlying product markets. To address this question, I examine the introduction of futures markets for two steel products in the U.S. in 2008 and 2012. The results show that futures markets reduce price dispersion and increase producers' hedging activity, consistent with improvements in market search and risk management. Additionally, the introduction of centralized futures markets heightens the sensitivity of market shares to production costs and decreases prices, as well as the profits and valuations of firms selling the affected products. Overall, these findings indicate that centralized derivative markets foster competition in the underlying product markets.

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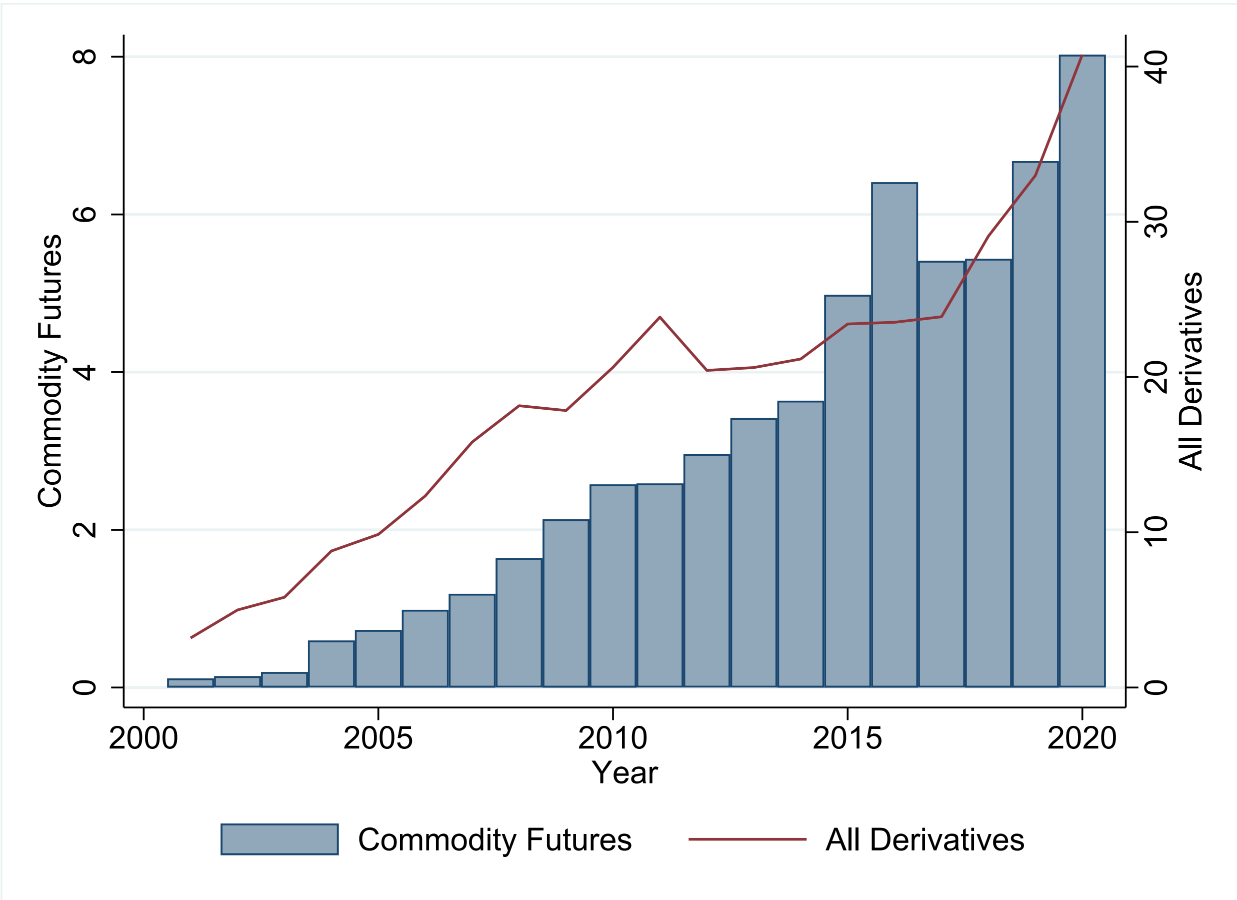
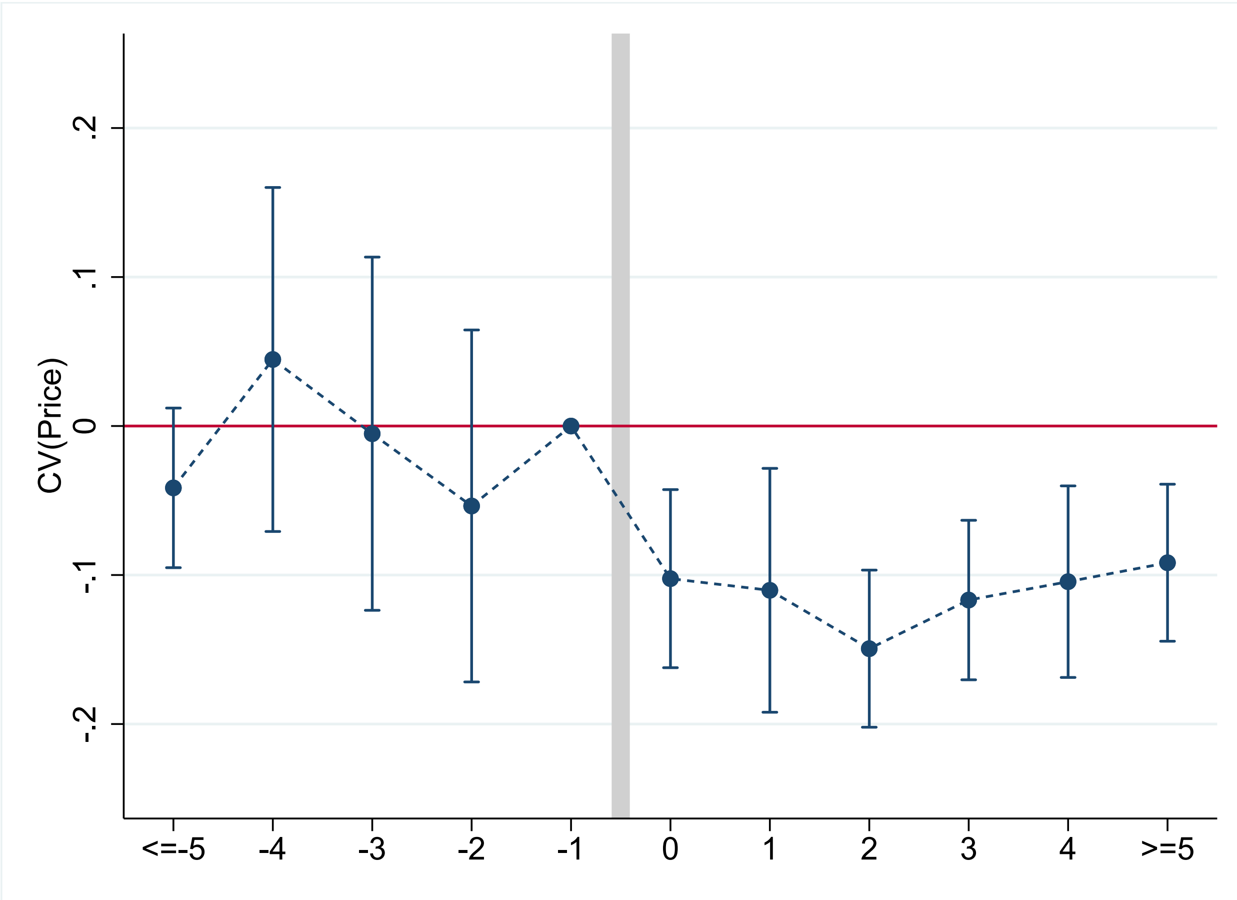
Figures

Figure 1: Growth of Exchange-Trading of Derivatives Over Time



This figure shows the evolution of global exchange-trading in derivatives (in billion contracts) for all derivatives (red line, right axis) and for commodity futures (blue bars, left axis). Source: World Federation of Exchanges.

Figure 2: Physical Product Market Price Dispersion - Dynamic Effects

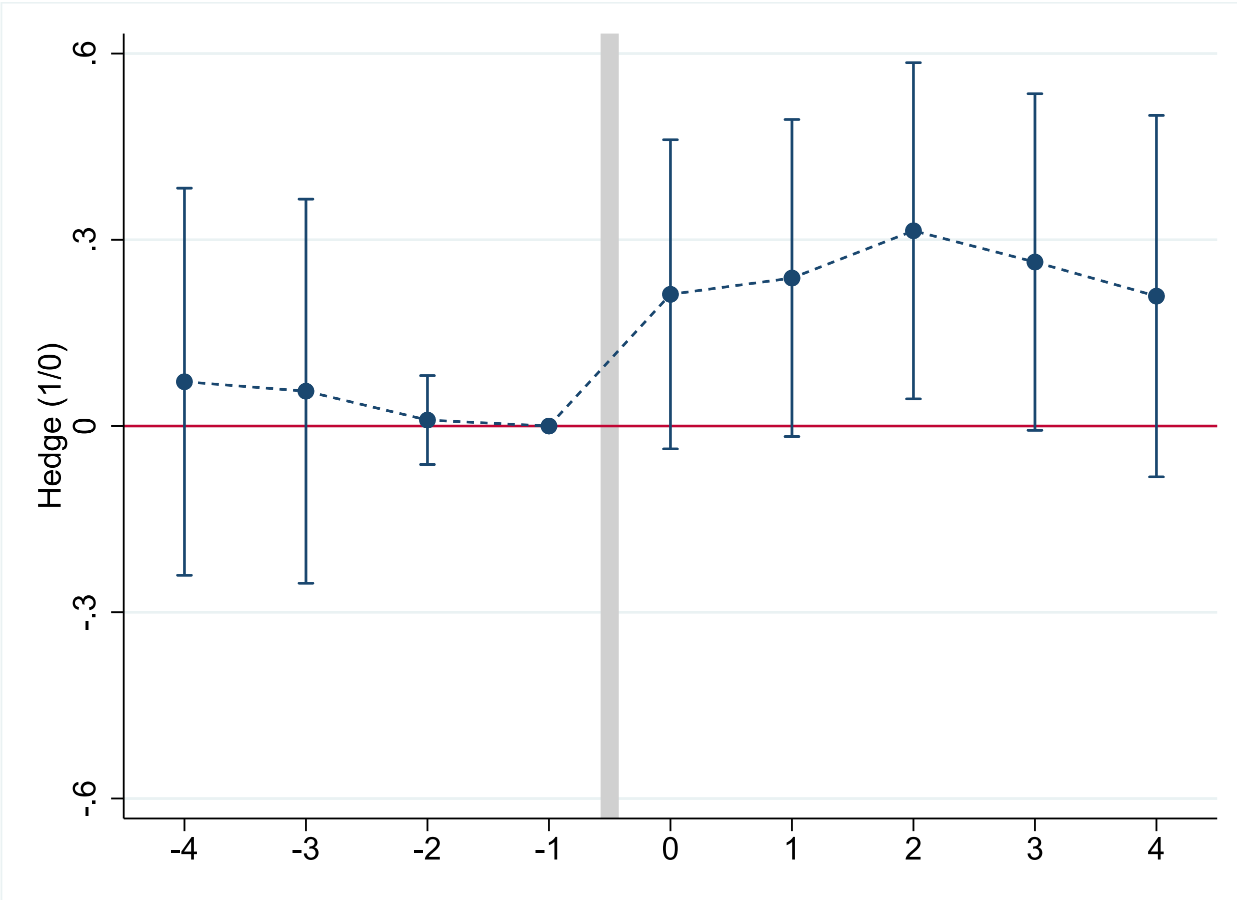


This figure shows estimates of the effect of centralized futures markets on price dispersion (*CV(Price)*) obtained from a difference-in-differences analysis around futures introductions. Specifically, the figure shows the estimated β_τ coefficients and 95% confidence intervals from the following regression:

$$\mathit{CV(Price)}_{k,p,t} = \sum_{\tau=-5}^{5} \left(\beta_\tau \mathit{Futures}_{product,k,p}\right) \mathbb{1}\left\{t = \tau\right\} + \alpha_{k,p} + \alpha_{k,t} + \varepsilon_{k,p,t}.$$

Futures introductions (HRC, BUS) are indexed by k, products by p, and publication dates by t. I combine publication dates $t \leqslant -5$ and $t \geqslant 5$ to one dummy respectively and use the last publication date before futures trading started as the reference date, omitting $\mathbb{1}\left\{t = -1\right\}$. $\mathit{Futures}_{product}$ is an indicator equal to one for hot-rolled coils (HRC) around the 2008 introduction of HRC futures and for busheling scrap (BUS) around the 2012 introduction of BUS futures. Control products are cold-rolled coil, plate, heavy-melting scrap, and shredded scrap. Standard errors are clustered by publication date.

Figure 3: Producer Commodity Hedging - Dynamic Effects

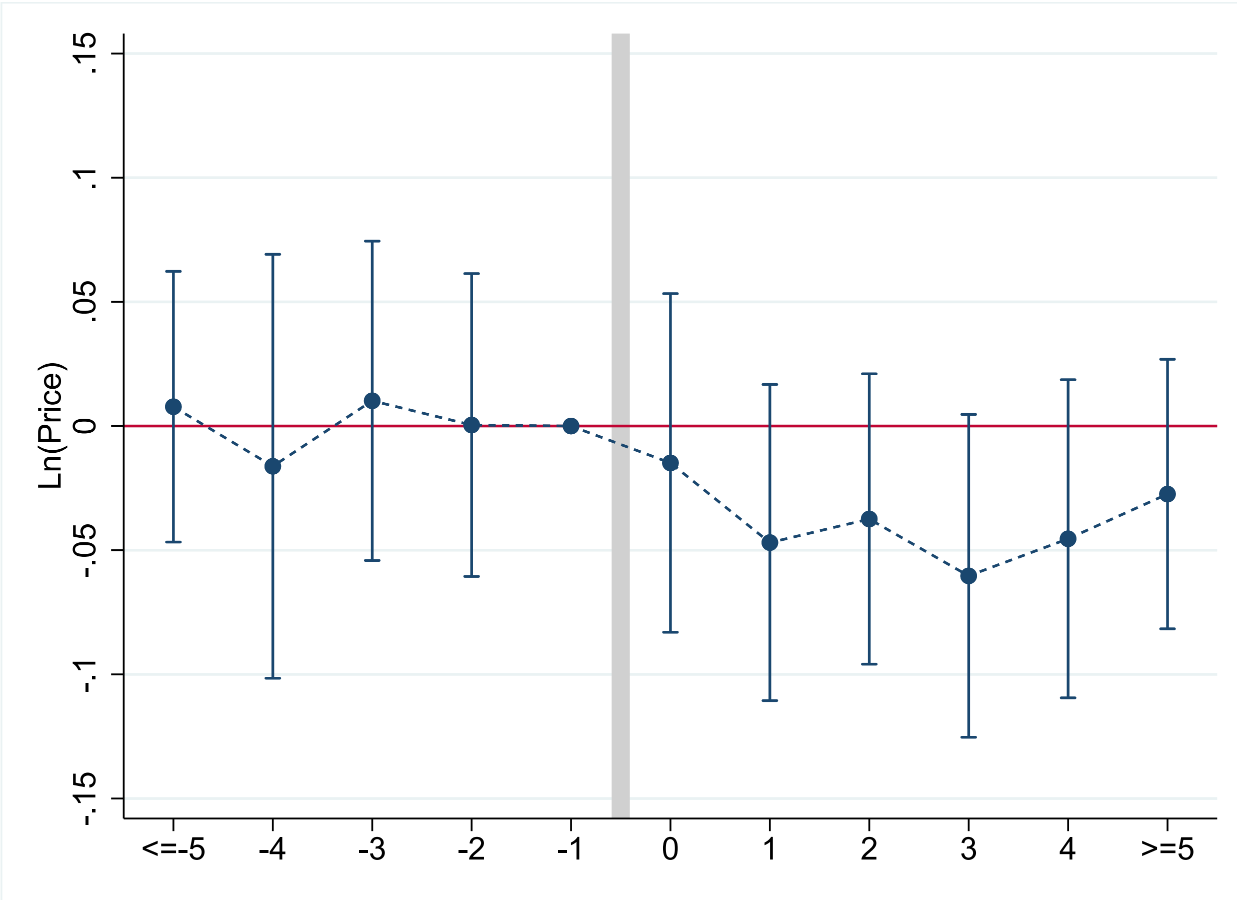


This figure shows estimates of the effect of centralized futures markets on firms' likelihood to discuss commodity hedging in their annual report (*Hedge (1/0)*) obtained from a difference-in-differences analysis around futures introductions. Specifically, the figure shows the estimated β_τ coefficients and 95% confidence intervals from the following regression:

$$\textit{Hedge (1/0)}_{k,i,y} = \sum_{\tau=-4}^{4} \left(\beta_\tau \textit{Futures}_{firm,k,i} + \theta'_\tau . X_{k,i}\right) \mathbb{1}\left\{y = \tau\right\} + \alpha_{k,i} + \alpha_{k,j,y} + \varepsilon_{k,i,y}.$$

Futures introductions (HRC, BUS) are indexed by k, and firms, 3-digit NAICS industries, and years by i, j, and y. I use the last year before futures trading started as the reference date, omitting $\mathbb{1}\left\{y = -1\right\}$. $\textit{Futures}_{firm}$ is an indicator equal to one for firms selling hot-rolled coil (HRC) around the 2008 introduction of HRC futures and for firms selling ferrous scrap around the 2012 introduction of busheling scrap futures (BUS). Standard errors are clustered by firm.

Figure 4: Physical Product Market Prices - Dynamic Effects

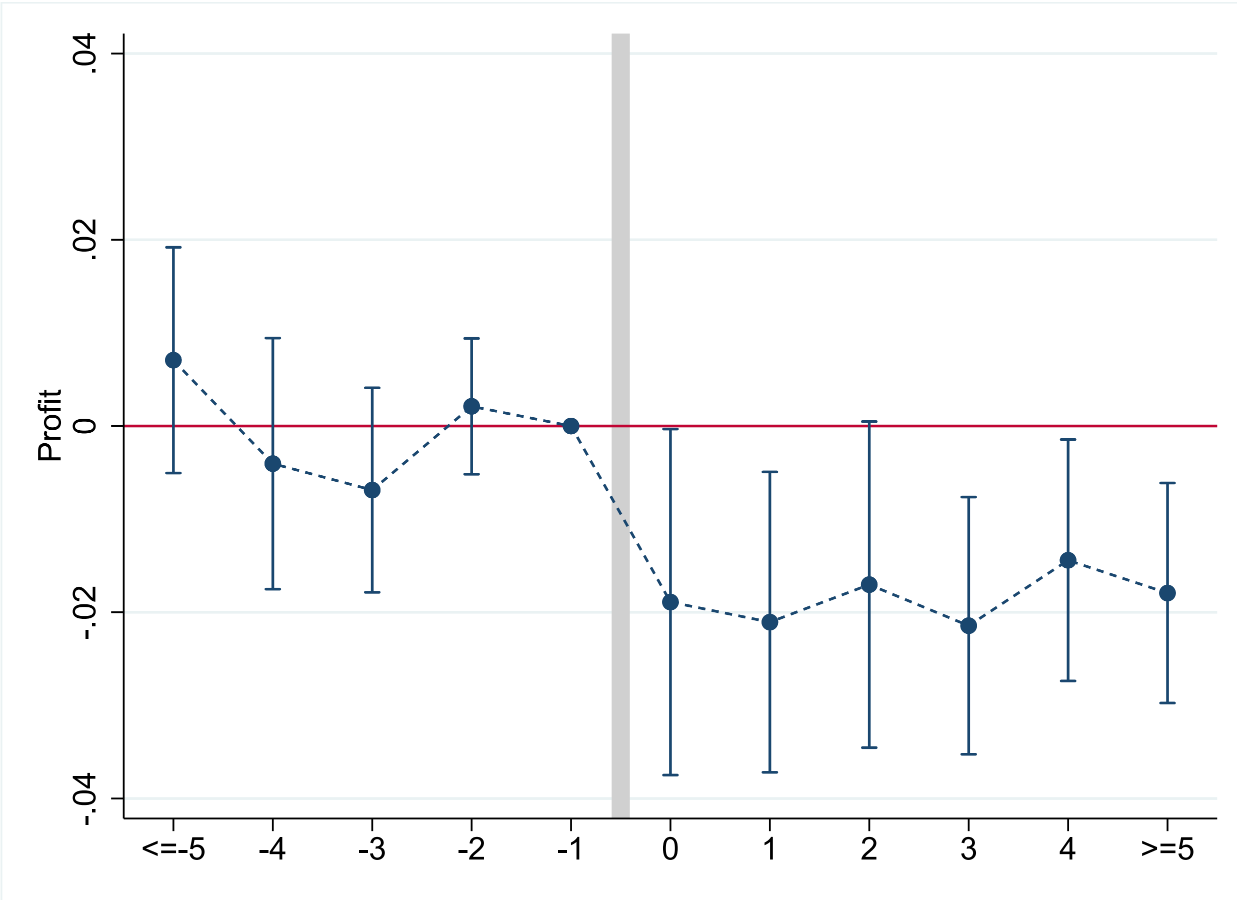


This figure shows estimates of the effect of centralized futures markets on physical product market prices (*Ln(Price)*) obtained from a difference-in-differences analysis around futures introductions. Specifically, the figure shows the estimated β_τ coefficients and 95% confidence intervals from the following regression:

$$\mathit{Ln(Price)}_{k,p,t} = \sum_{\tau=-5}^{5} \left(\beta_\tau \mathit{Futures}_{product,k,p}\right) \mathbb{1}\left\{t = \tau\right\} + \alpha_{k,p} + \alpha_{k,t} + \varepsilon_{k,p,t}.$$

Futures introductions (HRC, BUS) are indexed by k, products by p, and publication dates by t. I combine publication dates $t \leqslant -5$ and $t \geqslant 5$ to one dummy respectively and use the last publication date before futures trading started as the reference date, omitting $\mathbb{1}\left\{t = -1\right\}$. $\mathit{Futures}_{product}$ is an indicator equal to one for hot-rolled coils (HRC) around the 2008 introduction of HRC futures and for busheling scrap (BUS) around the 2012 introduction of BUS futures. Control products are cold-rolled coil, plate, heavy-melting scrap, and shredded scrap. Standard errors are clustered by publication date.

Figure 5: Producer Profits - Dynamic Effects

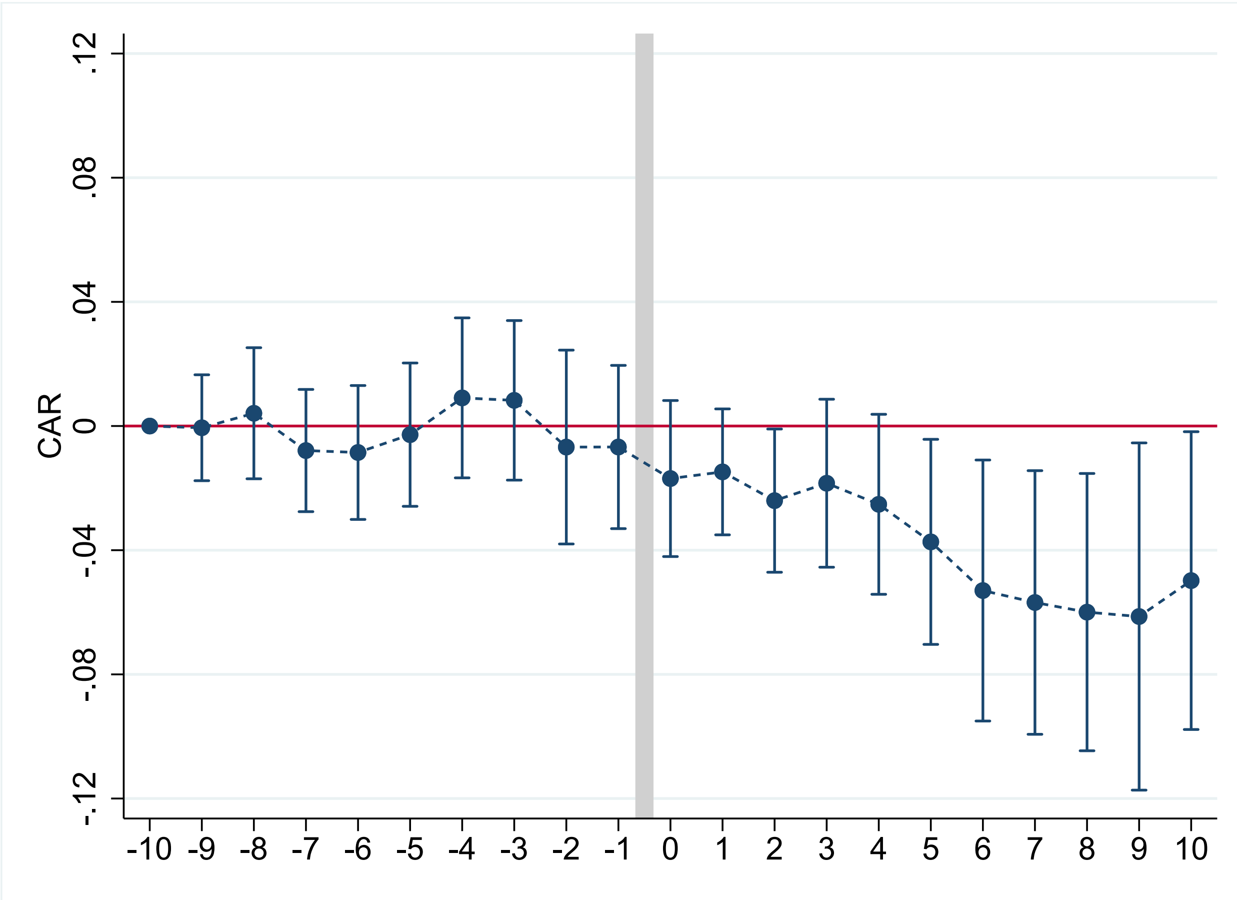


This figure shows estimates of the effect of centralized futures markets on firms' operating profits scaled by total assets (*Profit*) obtained from a difference-in-differences analysis around futures introductions. Specifically, the figure shows the estimated β_τ coefficients and 95% confidence intervals from the following regression:

$$Profit_{k,i,q} = \sum_{\tau=-5}^{5} \left(\beta_\tau Futures_{firm,k,i} + \theta'_\tau.X_{k,i}\right) \mathbb{1}\left\{q = \tau\right\} + \alpha_{k,i} + \alpha_{k,j,q} + \varepsilon_{k,i,q}.$$

Futures introductions (HRC, BUS) are indexed by k, and firms, 3-digit NAICS industries, and year-quarters by i, j, and q. I combine quarters $q \leqslant -5$ and $q \geqslant 5$ to one dummy respectively and use the last quarter before futures trading started as the reference date, omitting $\mathbb{1}\{q = -1\}$. $Futures_{firm}$ is an indicator equal to one for firms selling hot-rolled coil (HRC) around the 2008 introduction of HRC futures and for firms selling ferrous scrap around the 2012 introduction of busheling scrap futures (BUS). Standard errors are clustered by firm.

Figure 6: Event Study Around News Related to Futures Introductions



This figure shows estimates of the effect of centralized futures markets on firms' stock market valuations (*CAR*) obtained from a difference-in-differences analysis around news increasing the likelihood of futures contracts. Specifically, the figure shows the estimated β_τ coefficients and 95% confidence intervals from the following regression:

$$CAR_{e,i,d} = \sum_{\tau=-10}^{10} \left(\beta_\tau Futures_{firm,e,i}\right) \mathbb{1}\left\{d=\tau\right\} + \alpha_{e,i} + \alpha_{e,d} + \varepsilon_{e,i,d}.$$

Events are indexed by e, firms by i, and trading days in event time by d. I use the first day of the event window as the reference date, omitting $\mathbb{1}\left\{d=-10\right\}$. *CAR* is computed using the Carhart four factor model. $Futures_{firm}$ is an indicator equal to one for firms selling hot-rolled coil (HRC) on events relating to the 2008 introduction of HRC futures and for firms selling ferrous scrap on events relating to the 2012 introduction of busheling scrap futures (BUS). Standard errors are clustered by firm and trading day.

Tables

Table 1: Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)
Variable:	Obs.	Mean	SD	*p*1	*p*50	*p*99
Panel A: Product-level treatment and outcomes						
$\text{Futures}_{product}$	19,653	0.323	0.468	0.000	0.000	1.000
Price	19,653	709.814	224.202	339.480	705.000	1,315.000
Ln(Price)	19,653	6.514	0.324	5.827	6.558	7.182
SD(Price)	708	125.759	78.921	15.846	120.275	377.361
CV(Price)	708	0.187	0.108	0.038	0.171	0.515
Panel B: Firm-level treatment and outcomes						
Futures_{firm}	2,993	0.040	0.196	0.000	0.000	1.000
Hedge (1/0)	2,993	0.261	0.439	0.000	0.000	1.000
Market Share	1,419	0.085	0.136	0.001	0.031	0.717
Profit/Assets	5,095	0.028	0.025	-0.052	0.028	0.113
Panel C: Firm-level pre-period characteristics						
Assets (mn)	355	2,395	5,039	10	755	29,457
Firm Age	355	38.020	21.606	1.000	36.000	80.000
Sales Growth	355	0.022	0.158	-0.428	0.005	0.585
Panel D: Event study						
Futures_{firm}	1,106	0.040	0.196	0.000	0.000	1.000
$\text{CAR}_{market-adj.}$	1,106	-0.011	0.064	-0.215	-0.004	0.186
CAR_{CAPM}	1,106	-0.014	0.065	-0.225	-0.007	0.182
$\text{CAR}_{3-factor}$	1,106	-0.013	0.066	-0.228	-0.007	0.168
$\text{CAR}_{4-factor}$	1,106	-0.014	0.065	-0.222	-0.009	0.169

This table presents summary statistics for the variables used in the analysis. Internet Appendix E provides definitions.

Table 2: Physical Product Market Price Dispersion - DiD Estimation Around Futures Introductions

	(1)	(2)	(3)	(4)	(5)
Panel A:	SD(Price)				
Post×Futures$_{product}$	-38.636***	-34.695***	-32.220***	-35.349***	-30.339***
	(7.737)	(8.835)	(9.362)	(7.946)	(9.232)
R^2	0.769	0.773	0.770	0.770	0.775
Observations	708	708	708	708	708
Panel B:	CV(Price)				
Post×Futures$_{product}$	-0.057***	-0.057***	-0.059***	-0.058***	-0.056***
	(0.011)	(0.014)	(0.014)	(0.012)	(0.016)
R^2	0.676	0.677	0.676	0.676	0.678
Observations	708	708	708	708	708
Product FE	Yes	Yes	Yes	Yes	Yes
Publication Date FE	Yes	Yes	Yes	Yes	Yes
Demand Controls	No	Yes	No	No	Yes
Supply Controls	No	No	Yes	No	Yes
Trade Controls	No	No	No	Yes	Yes

This table presents estimates of the effect of centralized futures markets on physical product market price dispersion obtained from a difference-in-differences analysis around futures introductions. Price dispersion is measured for each publication date and product across different reporting firms using the standard deviation (*SD(Price)*) of price submissions in Panel A and the coefficient of variation (*CV(Price)*) in Panel B. *Futures*$_{product}$ is an indicator equal to one for hot-rolled coils (HRC) around the 2008 introduction of HRC futures and for busheling scrap (BUS) around the 2012 introduction of BUS futures. Control products are cold-rolled coil, plate, heavy-melting scrap, and shredded scrap. Prices are collected and published by *SteelBenchmarker* every two weeks. *Post* is an indicator equal to one for publication dates $t = 0, 1, \ldots, 40$, where $t = -1$ denotes the last publication date before the futures started trading. Column (2) adds controls to capture steel demand: quarterly GDP growth and output growth of key steel-consuming sectors (i.e., automotive, construction, machinery, appliances), interacted with the *Futures*$_{product}$ indicator (Source: Bureau for Economic Analyis). Column (3) adds controls to capture steel supply: annual growth rates of U.S. steel production (in metric tons) and capacity utilization, interacted with the *Futures*$_{product}$ indicator (Source: U.S. Geological Survey). Column (4) adds trade controls: annual growth rates of steel imports into the U.S. and global steel production, interacted with the *Futures*$_{product}$ indicator (Source: U.S. Geological Survey). Standard errors clustered by publication date are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table 3: Producer Commodity Hedging - DiD Estimation Around Futures Introductions

	(1)	(2)	(3)
	Hedge (1/0)		
Post$\times$Futures$_{firm}$	0.258***	0.248***	0.215**
	(0.089)	(0.091)	(0.096)
Firm FE	Yes	Yes	Yes
Year FE	Yes	No	No
Industry$\times$Year FE	No	Yes	Yes
Controls$\times$Year FE	No	No	Yes
R^2	0.689	0.695	0.701
Observations	2,993	2,993	2,993

This table presents estimates of the effect of centralized futures markets on producers' commodity hedging activity (*Hedge (1/0)*) obtained from a difference-in-differences analysis around futures introductions. *Hedge (1/0)* is an indicator equal to one for firms discussing usage of commodity derivatives in their annual report. *Futures*$_{firm}$ is an indicator equal to one for firms selling hot-rolled coil (HRC) around the 2008 introduction of HRC futures and for firms selling ferrous scrap around the 2012 introduction of busheling scrap futures (BUS). *Post* is an indicator equal to one in the years $y = 0, 1, \ldots, 4$, where $y = -1$ denotes the last year before the futures started trading. Controls are measured in the last quarter before the respective introduction and include the log of assets, firm age and sales growth. Standard errors clustered by firm are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table 4: Market Share Sensitivity to Cost - DiD Estimation Around Futures Introductions

	(1)	(2)	(3)
		Market Share	
Post$\times$Futures$_{firm}$$\times$EAF$\times$Iron/Scrap	0.054***	0.078***	0.073***
	(0.016)	(0.023)	(0.020)
Firm FE	Yes	Yes	Yes
Year-Quarter FE	Yes	No	No
Industry$\times$Year-Quarter FE	No	Yes	Yes
Controls$\times$Year-Quarter FE	No	No	Yes
Interactions	Yes	Yes	Yes
Sample	HRC	HRC	HRC
R^2	0.980	0.980	0.981
Observations	1,419	1,419	1,419

This table presents estimates of the effect of centralized futures markets on the sensitivity of market share (*Market Share*) to cost obtained from a difference-in-differences analysis around the hot-rolled coil (HRC) futures introduction. *Futures*$_{firm}$ is an indicator equal to one for firms selling HRC around the 2008 introduction of HRC futures. *Post* is an indicator equal to one in the quarters $q = 0, 1, \ldots, 7$, where $q = -1$ denotes the last quarter before the futures started trading. *EAF* is an indicator equal to one for electric arc furnace (EAF) producers. EAF producers use steel scrap as their primary raw material whereas basic oxygen furnace (BOF) producers use primarily iron ore. *Iron/Scrap* is the quarterly ratio of iron ore to scrap prices. Controls are measured in $q = -1$ and include the log of assets, firm age and sales growth. Standard errors clustered by firm are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table 5: Physical Product Market Prices - DiD Estimation Around Futures Introductions

	(1)	(2)	(3)	(4)	(5)
	Ln(Price)				
Post$\times$Futures$_{product}$	-0.036***	-0.032***	-0.039***	-0.036***	-0.040***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.007)
Product FE	Yes	Yes	Yes	Yes	Yes
Publication Date FE	Yes	Yes	Yes	Yes	Yes
Demand Controls	No	Yes	No	No	Yes
Supply Controls	No	No	Yes	No	Yes
Trade Controls	No	No	No	Yes	Yes
R^2	0.917	0.917	0.917	0.917	0.918
Observations	19,653	19,653	19,653	19,653	19,653

This table presents estimates of the effect of centralized futures markets on physical product market prices (*Ln(Price)*) obtained from a difference-in-differences analysis around futures introductions. *Futures*$_{product}$ is an indicator equal to one for hot-rolled coils (HRC) around the 2008 introduction of HRC futures and for busheling scrap (BUS) around the 2012 introduction of BUS futures. Control products are cold-rolled coil, plate, heavy-melting scrap, and shredded scrap. Prices are collected and published by *SteelBenchmarker* every two weeks. *Post* is an indicator equal to one for publication dates $t = 0, 1, \ldots, 40$, where $t = -1$ denotes the last publication date before the futures started trading. Column (2) adds controls to capture steel demand: quarterly GDP growth and output growth of key steel-consuming sectors (i.e., automotive, construction, machinery, appliances), interacted with the *Futures*$_{product}$ indicator (Source: Bureau for Economic Analyis). Column (3) adds controls to capture steel supply: annual growth rates of U.S. steel production (in metric tons) and capacity utilization, interacted with the *Futures*$_{product}$ indicator (Source: U.S. Geological Survey). Column (4) adds trade controls: annual growth rates of steel imports into the U.S. and global steel production, interacted with the *Futures*$_{product}$ indicator (Source: U.S. Geological Survey). Standard errors clustered by publication date are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table 6: Producer Profits - DiD Estimation Around Futures Introductions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Profit						
Post×Futures$_{firm}$	-0.016***	-0.019***	-0.021***	-0.022***	-0.019***	-0.019***	-0.019***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Business Cycle Controls	No	No	Yes	Yes	Yes	Yes	Yes
Iron/Scrap Price Controls	No	No	No	Yes	Yes	Yes	Yes
Import Controls	No	No	No	No	Yes	Yes	Yes
Segment Controls	No	No	No	No	No	Yes	Yes
Excluding M&A	No	No	No	No	No	No	Yes
R^2	0.602	0.629	0.652	0.669	0.670	0.677	0.684
Observations	5,095	5,095	4,953	4,942	4,942	4,942	4,591

This table presents estimates of the effect of centralized futures markets on producers' operating profits scaled by total assets (*Profit*) obtained from a difference-in-differences analysis around futures introductions:

$$Profit_{k,i,q} = \beta.Post.Futures_{firm,k,i} + \sum_{\tau=-7}^{7} \left(\theta'_{\tau}.X_{k,i}\right) \mathbb{1}\left\{q = \tau\right\} + \alpha_{k,i} + \alpha_{k,j,q} + \varepsilon_{k,i,q}.$$

Futures introductions (HRC, BUS) are indexed by k, firms by i, year-quarters by q, and 3-digit NAICS industries by j. *Profit*$_{k,i,q}$ is the operating profit of firm i in year-quarter q scaled by beginning-of-quarter total assets. *Futures*$_{firm}$ is an indicator equal to one for firms selling hot-rolled coil (HRC) around the 2008 introduction of HRC futures and for firms selling ferrous scrap around the 2012 introduction of busheling scrap futures (BUS). *Post* is an indicator equal to one in the quarters $q = 0, 1, \ldots, 7$, where $q = -1$ denotes the last quarter before the futures started trading. Column (2) adds the baseline controls (log of assets, firm age, and sales growth, measured in $q = -1$ and interacted with the time fixed effects). Column (3) adds business cycle controls (firms' sales beta with respect to aggregate GDP, automotive, construction, machinery, and appliance sector growth all interacted with the time fixed effects), Column (4) adds controls for iron ore and scrap prices (firms' profit and input cost beta with respect to iron ore relative to scrap prices and a dummy for *EAF* producers, all interacted with the time fixed effects, as well as interactions of the *Futures*$_{firm}$ dummy with the quarterly ratio of iron ore to scrap prices and with the log of quarterly iron ore prices), Column (5) adds import competition controls (the *Futures*$_{firm}$ dummy interacted with industry-level import competition from all countries and from China, India, and Japan), and Column (6) adds segment controls (the share of foreign sales and the share of sales in the main industry interacted with time fixed effects). Column (7) excludes observations involved in M&A activity. Standard errors clustered by firm are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table 7: Event Study Around News Related to Futures Introductions

	(1)	(2)	(3)	(4)
	CAR$_{-2,+2}$			
Futures$_{firm}$	-0.049***	-0.037***	-0.039***	-0.039***
	(0.010)	(0.012)	(0.015)	(0.013)
Firm FE	Yes	Yes	Yes	Yes
Event Date FE	Yes	Yes	Yes	Yes
Model	Market-adj.	CAPM	3-factor	4-factor
R^2	0.257	0.241	0.225	0.233
Observations	1,106	1,106	1,106	1,106

This table presents OLS estimates of regressing producers' cumulative abnormal returns (*CAR*) during the five-day window around news increasing the likelihood of hot-rolled coil (HRC) and busheling scrap (BUS) futures on an indicator variable for affected firms: *Futures*$_{firm}$ is an indicator equal to one for firms selling hot-rolled coil (HRC) on events relating to the 2008 introduction of HRC futures and for firms selling ferrous scrap on events relating to the 2012 introduction of busheling scrap futures (BUS). Standard errors clustered by firm are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table 8: Separate DiD Estimation Around HRC and BUS Futures Introductions

	(1)	(2)	(3)	(4)	(5)
Panel A: HRC	SD(Price)	CV(Price)	Hedge (1/0)	Ln(Price)	Profit
Post×Futures$_{product}$	-55.875***	-0.049***		-0.034***	
	(13.249)	(0.015)		(0.005)	
Post×Futures$_{firm}$			0.206*		-0.023**
			(0.120)		(0.009)
R^2	0.841	0.894	0.652	0.900	0.648
Observations	222	222	1,551	8,856	2,508
Panel B: BUS	SD(Price)	CV(Price)	Hedge (1/0)	Ln(Price)	Profit
Post×Futures$_{product}$	-26.081***	-0.064***		-0.038***	
	(6.241)	(0.012)		(0.008)	
Post×Futures$_{firm}$			0.301**		-0.018***
			(0.127)		(0.006)
R^2	0.523	0.440	0.721	0.921	0.720
Observations	486	486	1,442	10,797	2,434
Product FE	Yes	Yes	No	Yes	No
Publication Date FE	Yes	Yes	No	Yes	No
Firm FE	No	No	Yes	No	Yes
Year FE	No	No	Yes	No	No
Industry×Year-Quarter FE	No	No	No	No	Yes
Controls×Year-Quarter	No	No	No	No	Yes

This table presents the main results separately for the hot-rolled coil (Panel A) and busheling scrap (Panel B) futures introductions. *Futures*$_{product}$ is an indicator equal to one for hot-rolled coils (HRC) around the 2008 introduction of HRC futures and for busheling scrap (BUS) around the 2012 introduction of BUS futures. *Futures*$_{firm}$ is an indicator equal to one for firms selling HRC around the 2008 introduction of HRC futures and for firms selling ferrous scrap around the 2012 introduction of BUS futures. *Post* is an indicator equal to one after futures started trading. Standard errors clustered by publication date in Columns (1), (2), and (4) and by firm in Columns (3) and (5) are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table 9: Placebo Tests - DiD Estimation Around Futures Introductions - non-U.S. Producers

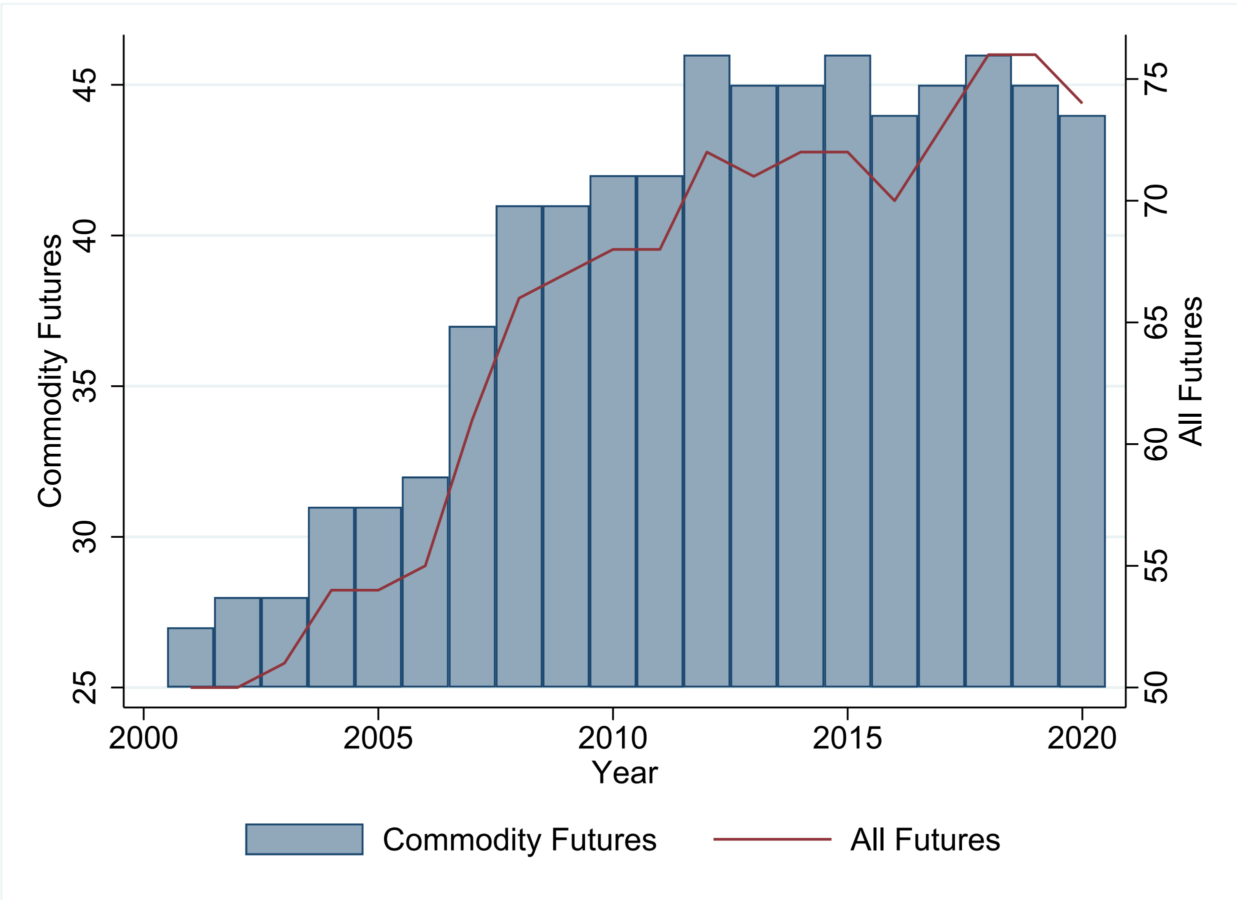
	(1)	(2)	(3)	(4)
	Hedge (1/0)	Market Share	Profit	$CAR_{-2,+2}$
Post×Futures_{firm}	0.009		-0.000	
	(0.067)		(0.003)	
Post×Futures_{firm}×EAF×Iron/Scrap		0.008		
		(0.023)		
Futures_{firm}				-0.004
				(0.022)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No
Year-Quarter FE	No	Yes	Yes	No
Interactions	No	Yes	No	No
Event Date FE	No	No	No	Yes
R^2	0.719	0.943	0.661	0.316
Observations	4,054	2,394	7,303	1,804

This table presents placebo tests in a sample of non-U.S. firms. Columns (1) to (4) estimate specifications akin to Column (1) of Tables 3, 4, 6, and 7 in a sample of non-U.S. producers, operating in countries without steel futures introduction during the sample period (excluding China, India, South Korea, Turkey, the UAE, and the Black Sea region). *Futures*$_{firm}$ is an indicator equal to one for firms selling HRC around the 2008 introduction of HRC futures and for firms selling ferrous scrap around the 2012 introduction of BUS futures. *Post* is an indicator equal to one after the HRC and BUS futures started trading in the US. *EAF* is an indicator equal to one for electric arc furnace (EAF) producers. EAF producers use steel scrap as their primary raw material whereas basic oxygen furnace (BOF) producers use primarily iron ore. *Iron/Scrap* is the quarterly ratio of iron ore to scrap prices. The sample in Column (2) is restricted to the HRC introduction. Standard errors clustered by firm are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Internet Appendix to
"Real Effects of Centralized Markets: Evidence from Steel Futures"

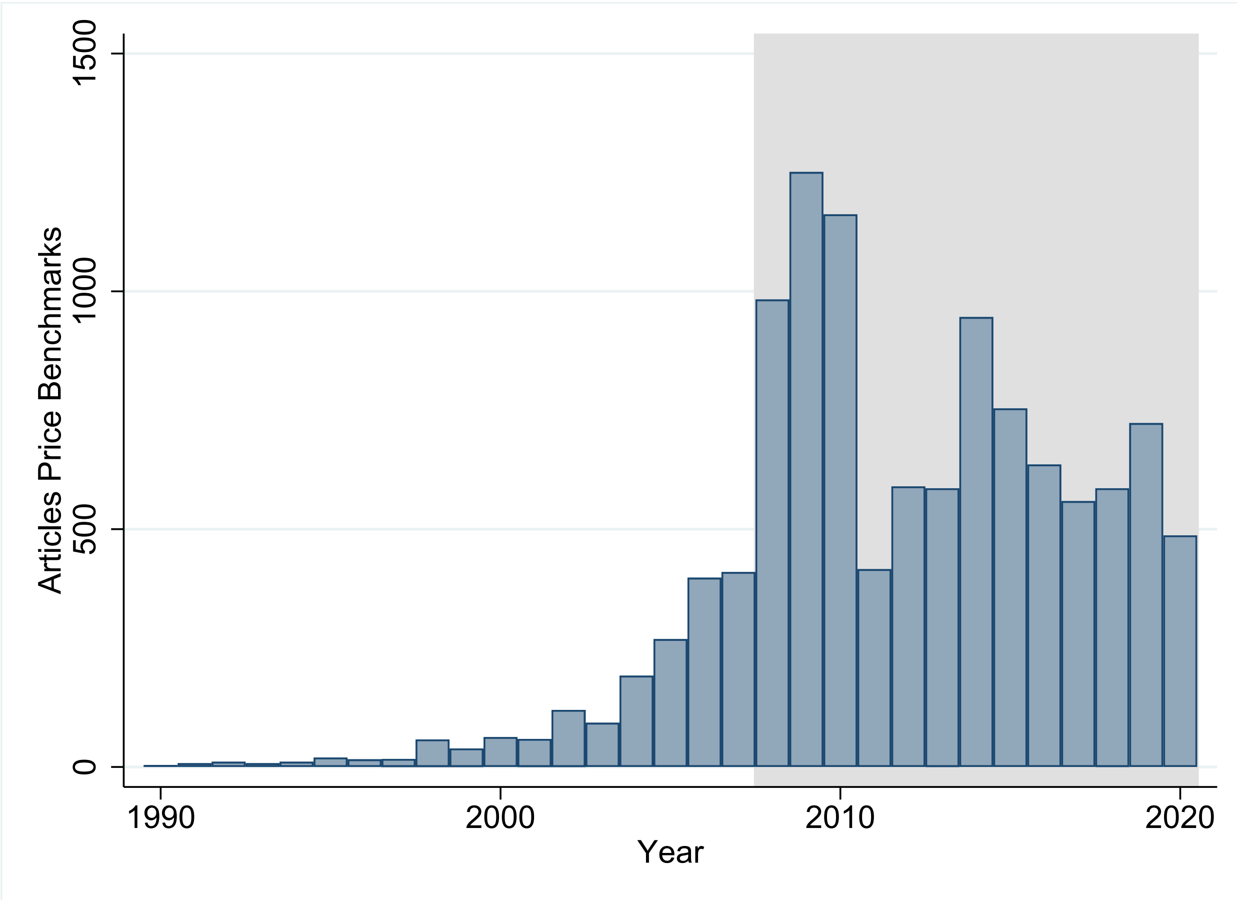
A Supplemental Analyses

Figure A.1: Number of Distinct Products Covered in Commitment of Traders Report



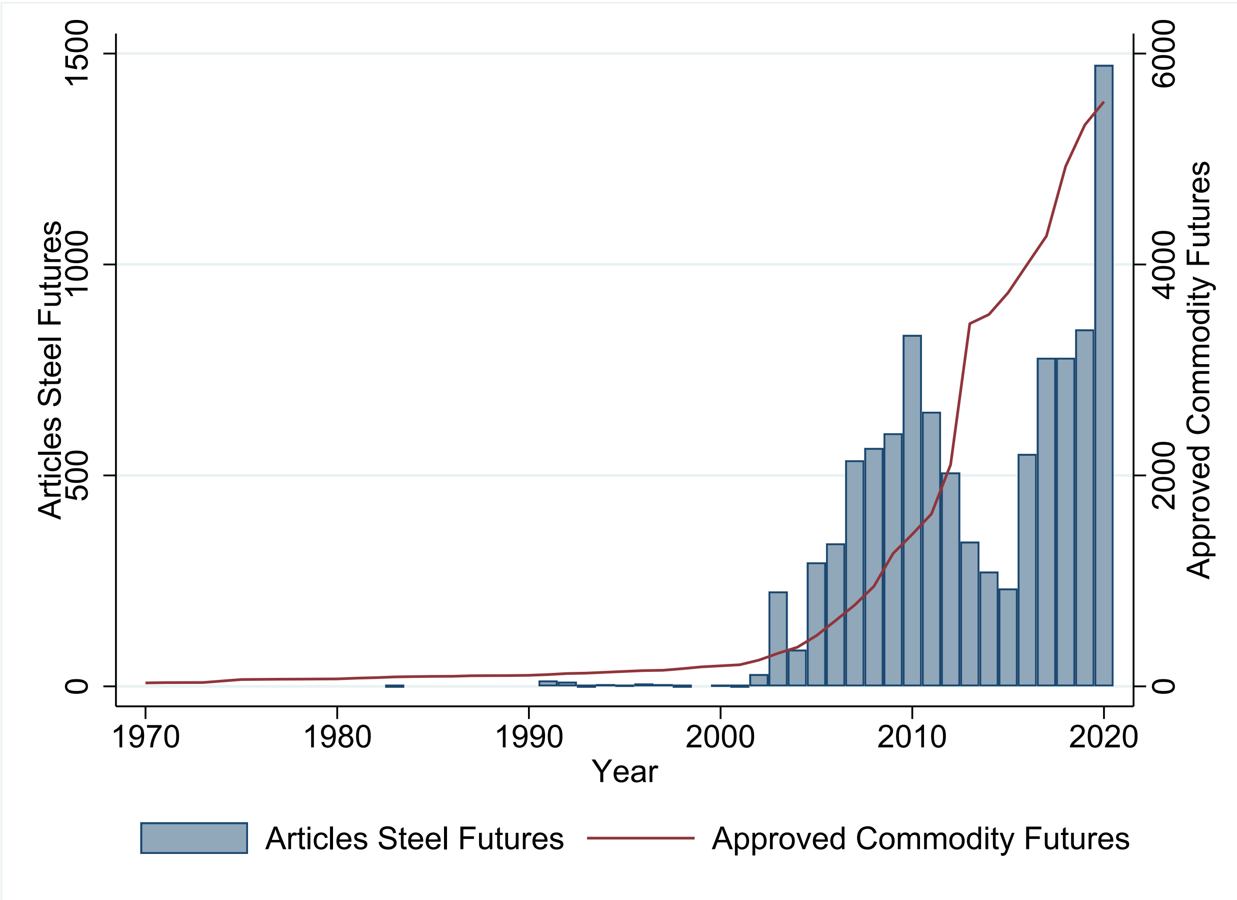
This figure shows the number of distinct products appearing in the commitment of traders (COT) report of the Commodity Futures Trading Commission (CFTC) for all futures covered (red line, right axis) and for commodity futures (blue bars, left axis). The COT report covers all futures in which 20 or more traders hold positions above reporting thresholds established by the CFTC. Products are identified by CFTC commodity codes. Source: CFTC.

Figure A.2: Steel Price Benchmark Keywords in the Media



This figure shows the number of newspaper articles mentioning either steel or ferrous scrap along with price benchmark keywords over time. Price benchmark keywords include "price benchmark", "reference price", and "price transparency". I require that these keywords appear in the same paragraph as either steel or ferrous scrap. The shaded area indicates the years 2008 onward. Source: Factiva.

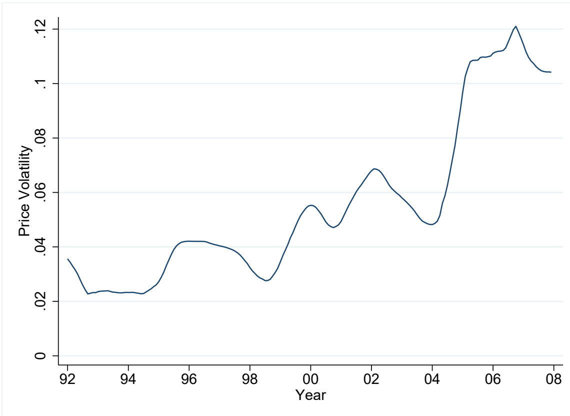
Figure A.3: Steel Futures in the Media and Number of Futures Approved by CFTC



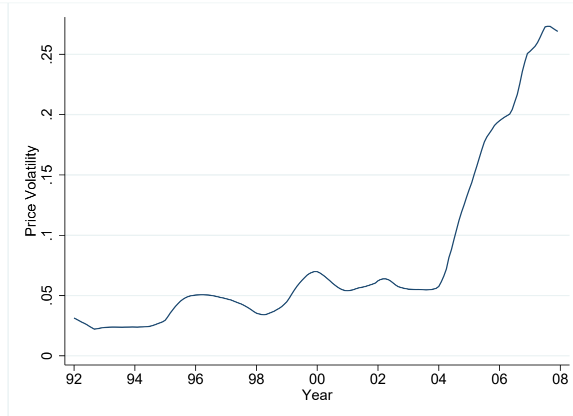
This figure shows the number of commodity futures approved by the Commodity Futures Trading Commission (CFTC) (red line, right axis) and the number of newspaper articles mentioning steel futures (blue bars, left axis) from 1970 to 2020. Source: CFTC, Factiva.

Figure A.4: Steel Price Volatility by Product Group Before First NYMEX Futures Contracts

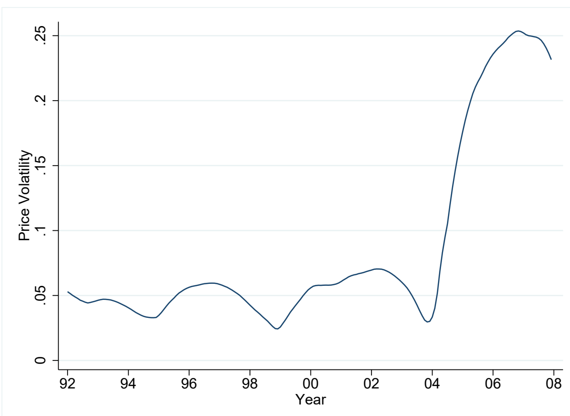
(a) Hot rolled steel sheet and strip



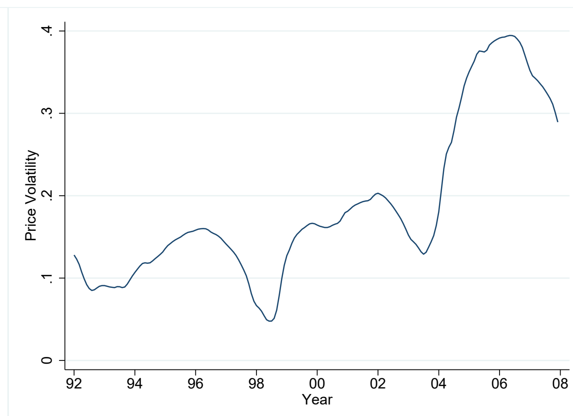
(b) Cold rolled steel sheet and strip



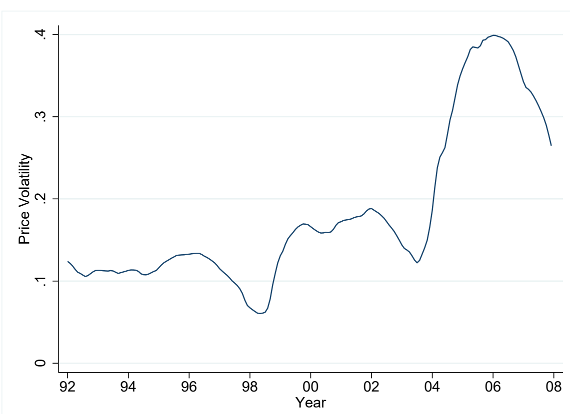
(c) Hot rolled steel bars, plates, and structural shapes



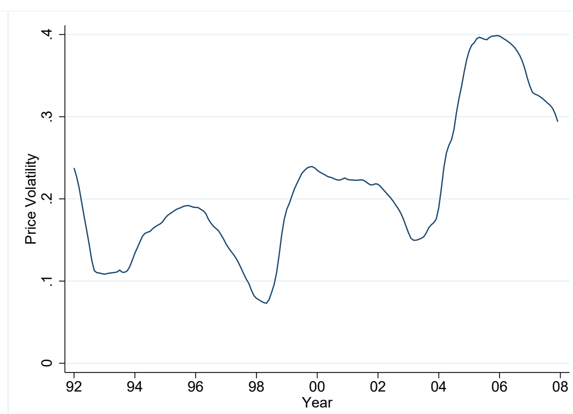
(d) Heavy melting scrap



(e) Shredded carbon steel scrap

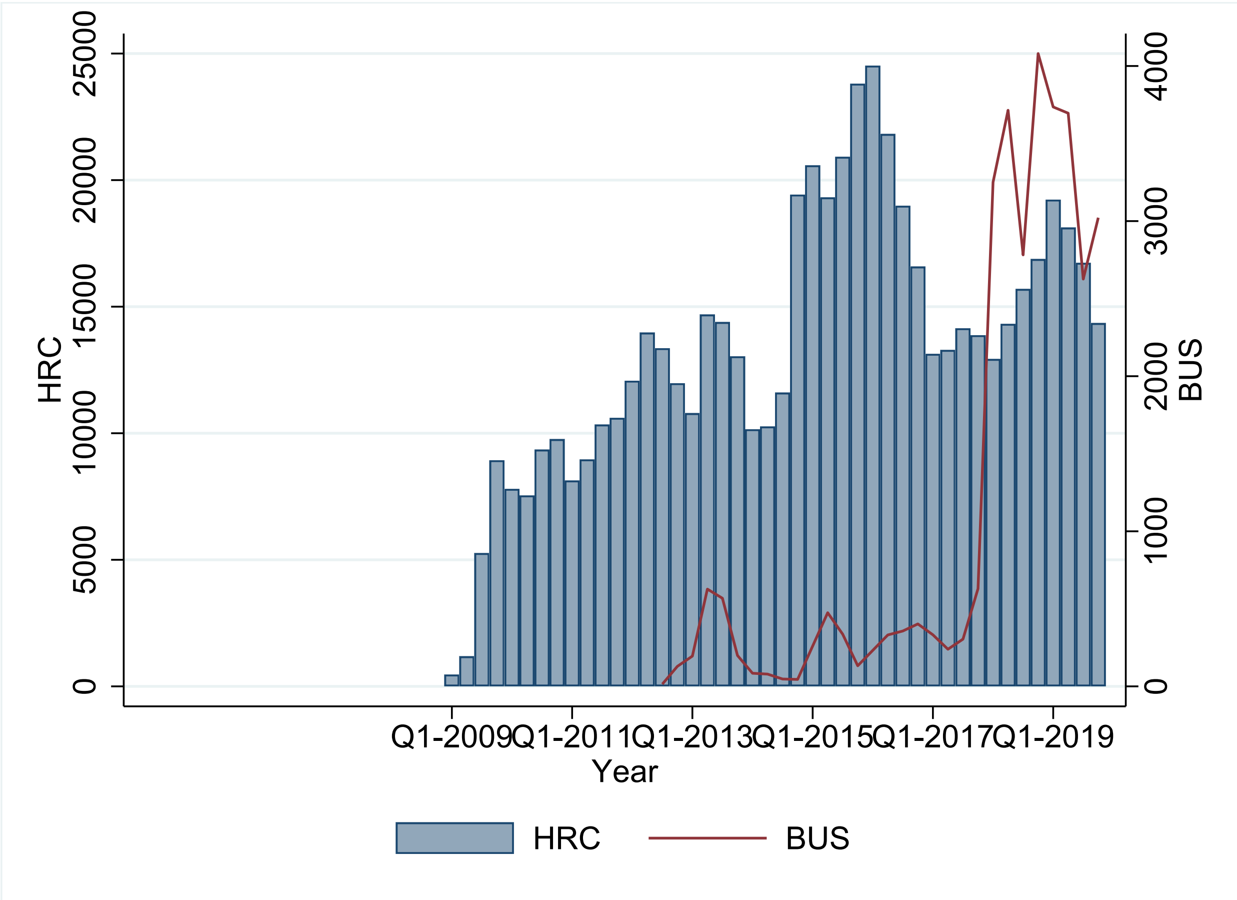


(f) Other carbon steel scrap



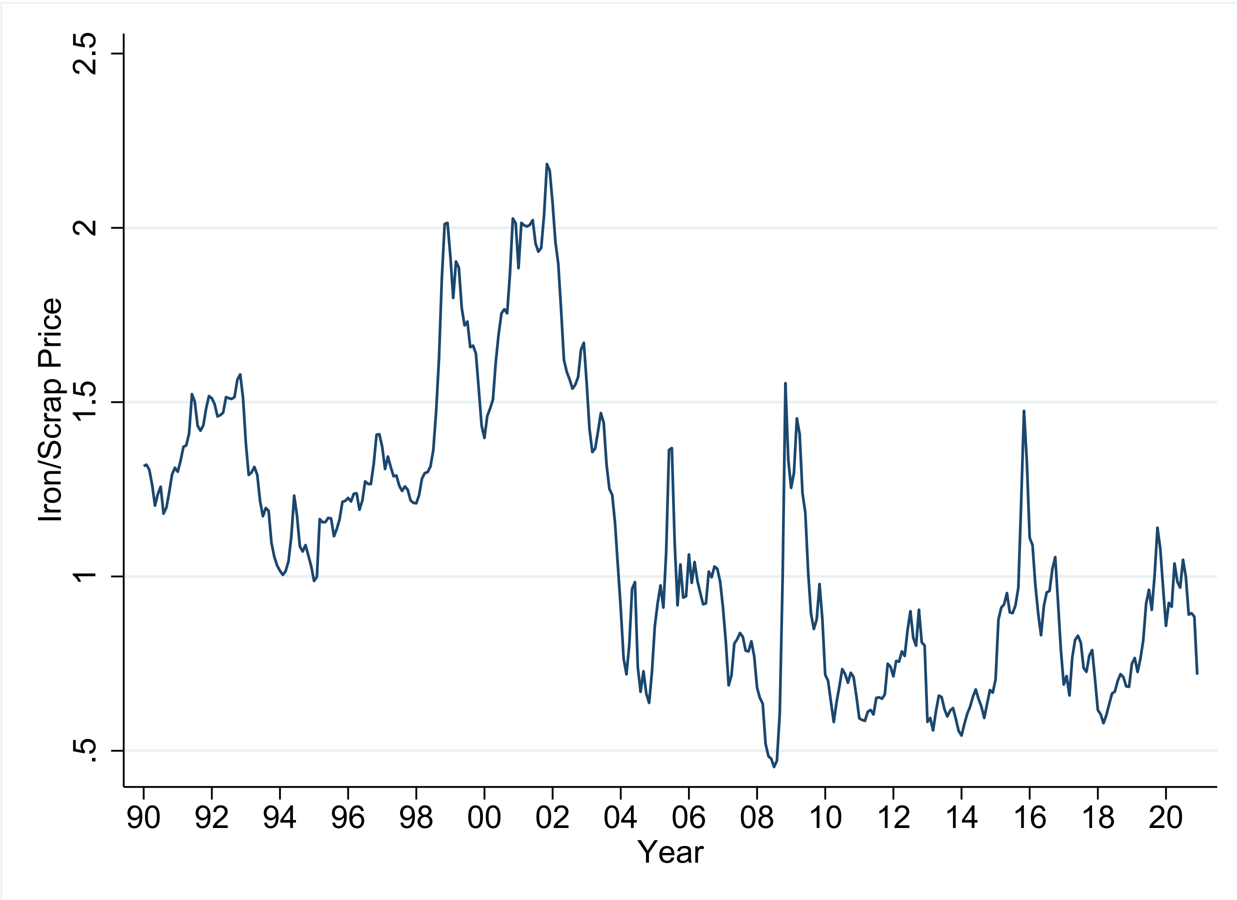
This figure shows price volatility for different steel product categories from 1992 to 2007. Price volatility is measured as the 5-year rolling standard deviation of the monthly log price index of the product category indicated above each graph. Hot rolled coils (HRC) are part of the product category "Hot rolled steel sheet and strip" and busheling scrap (BUS) is part of the product category "Other carbon steel scrap". Source: BLS Producer Price Index Series.

Figure A.5: Open Interest NYMEX Steel Futures



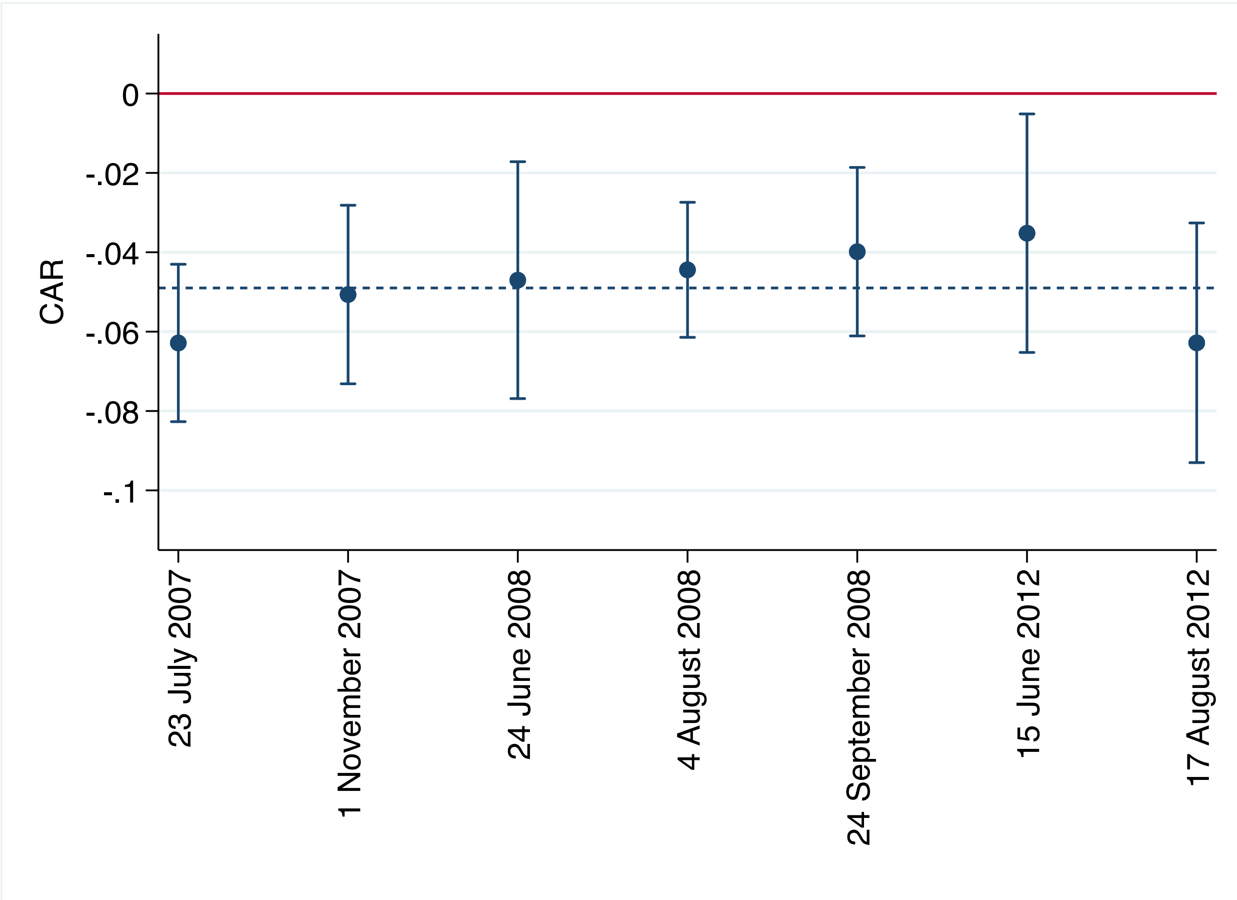
This figure shows the open interest (in number of contracts) of the NYMEX steel futures for hot-rolled coils (HRC) (blue bars, left axis) and for busheling scrap (BUS) (red line, right axis) over time. The contract unit for HRC (BUS) is 20 short tons (20 gross tons). Source: Bloomberg.

Figure A.6: Iron/Scrap Prices



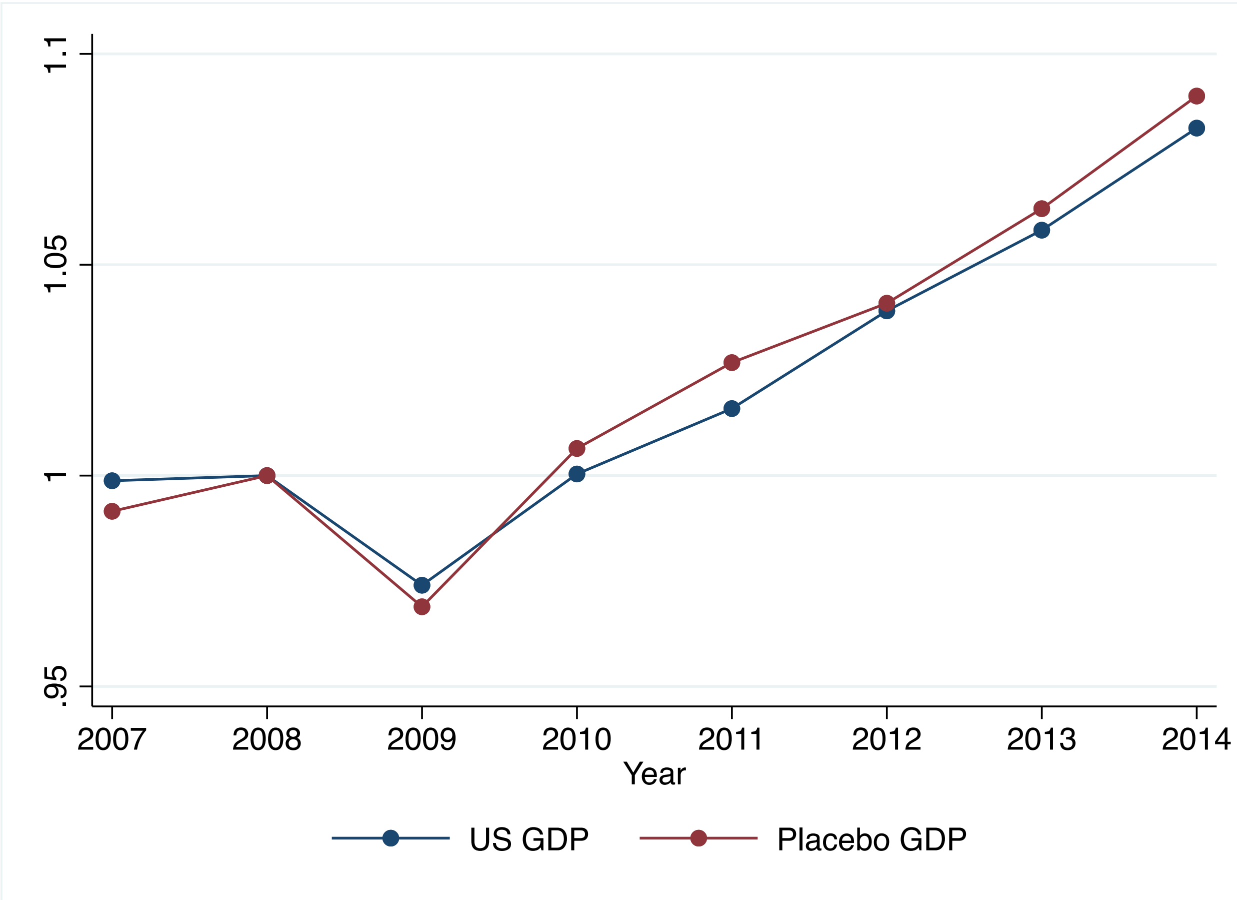
This figure shows the evolution of iron ore prices (WPS1011) relative to scrap prices (WPS1012) from 1990 to 2020. The time series is normalized to 1 for the first observation available (January 1947). Source: BLS Producer Price Index Series.

Figure A.7: Event Study Robustness: Leave-One-Out



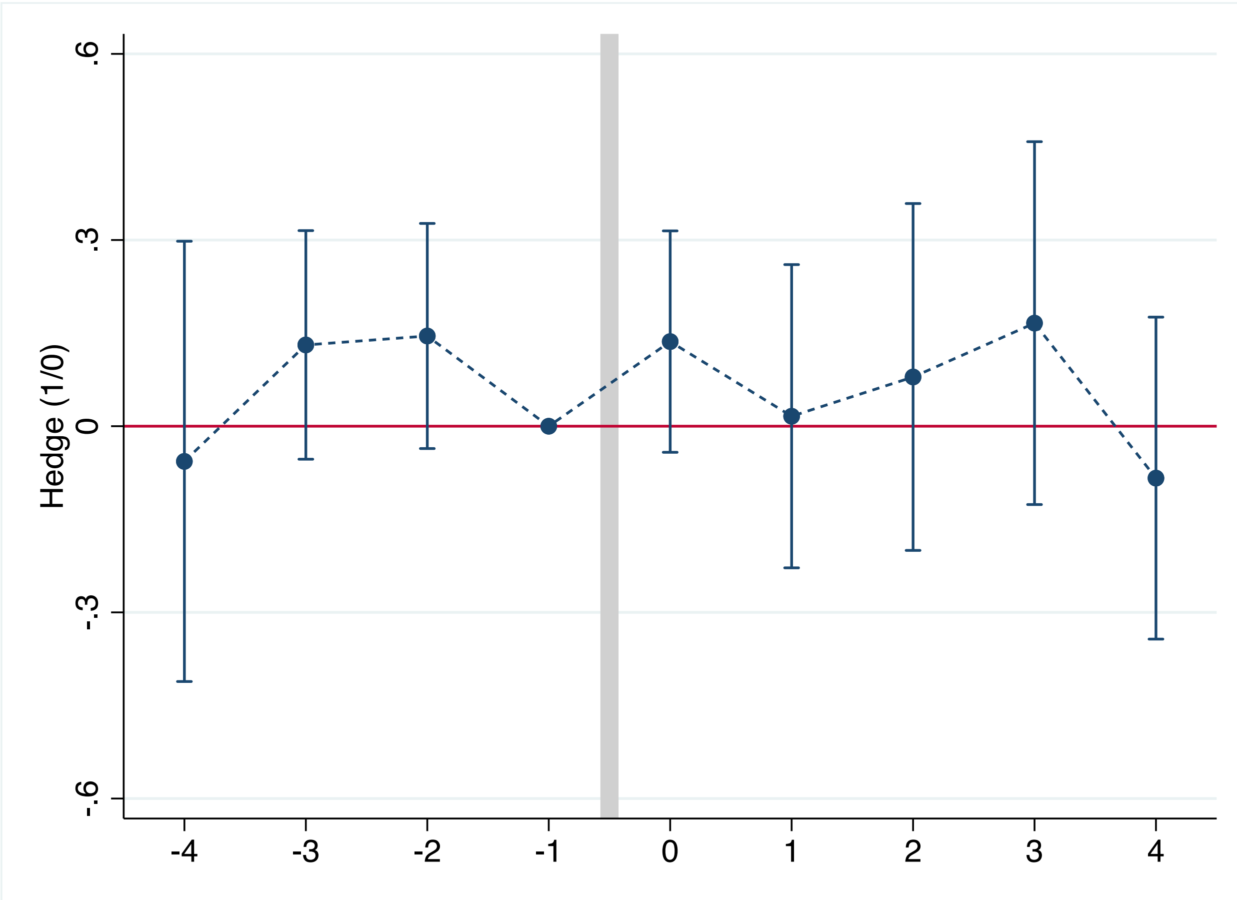
This figure displays leave-one-out specifications of the event study estimates shown in Column (1) of Table 7. The graph shows the point estimates and 95% confidence intervals of regressing producers' cumulative abnormal returns (*CAR*) on the $Futures_{firm}$ indicator, leaving out the event date indicated on the x-axis. *CAR* is measured during the five-day window around news increasing the likelihood of futures contracts. $Futures_{firm}$ is an indicator equal to one for firms selling hot-rolled coil (HRC) on events relating to the 2008 introduction of HRC futures and for firms selling ferrous scrap on events relating to the 2012 introduction of busheling scrap futures (BUS). The dotted line shows the point estimate when all event dates are included (-0.049). Standard errors are clustered by firm.

Figure A.8: GDP of U.S. and Placebo Countries



This figure shows the evolution of real GDP for the U.S. and the countries in the placebo sample over the sample period 2007–2014. GDP is normalized to 1 in 2008. Placebo GDP is the sales-weighted average GDP across firms in the placebo sample. Sales weights are measured in USD in Q4-2007. The placebo sample consists of non-U.S. producers, operating in countries without steel futures introduction during the sample period (excluding China, India, South Korea, Turkey, the UAE, and the Black Sea region). GDP data is from the IMF World Economic Outlook, sales data are from Compustat Global, and the share of firms' sales across countries is from FactSet GeoRev.

Figure A.9: Placebo Test: non-U.S. Producer Commodity Hedging

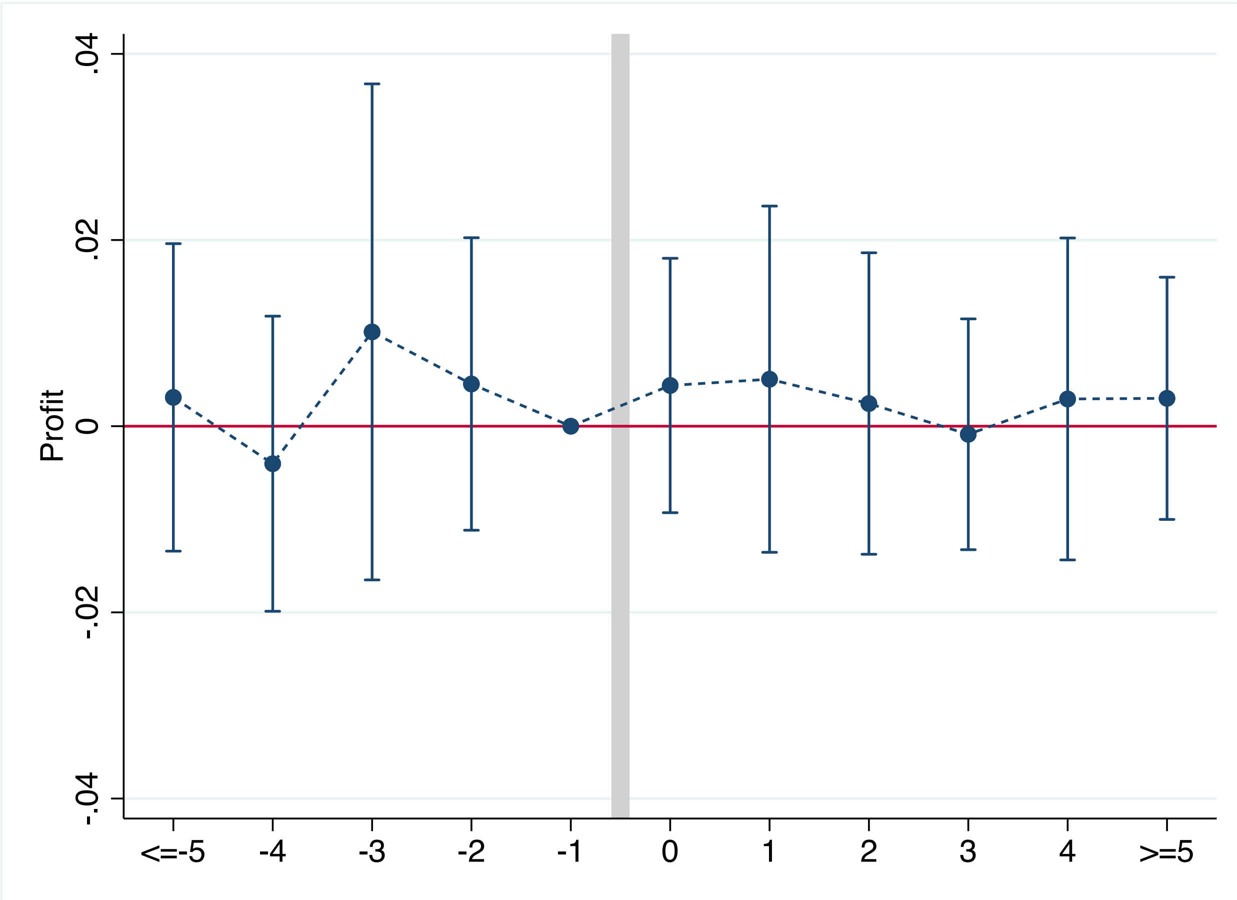


This figure shows placebo estimates of the effect of centralized futures markets on firms' likelihood to discuss commodity hedging in their annual report (*Hedge (1/0)*) obtained from a difference-in-differences analysis around U.S. futures introductions in a sample of non-U.S. steel producers. Specifically, the figure shows the estimated β_τ coefficients and 95% confidence intervals from the following regression:

$$\textit{Hedge (1/0)}_{k,i,y} = \sum_{\tau=-4}^{4} \left(\beta_\tau \textit{Futures}_{firm,k,i} + \theta'_\tau . X_{k,i}\right) \mathbb{1}\left\{y = \tau\right\} + \alpha_{k,i} + \alpha_{k,c,j,y} + \varepsilon_{k,i,y}.$$

Futures introductions (HRC, BUS) are indexed by k, and firms, headquarter countries, 3-digit NAICS industries, and years by i, c, j, and y. I use the last year before futures trading started as the reference date, omitting $\mathbb{1}\left\{y = -1\right\}$. The sample consists of non-U.S. producers, operating in countries without steel futures introduction during the sample period (excluding China, India, South Korea, Turkey, the UAE, and the Black Sea region). $\textit{Futures}_{firm}$ is an indicator equal to one for firms selling hot-rolled coil (HRC) around the 2008 introduction of HRC futures and for firms selling ferrous scrap around the 2012 introduction of busheling scrap futures (BUS). Standard errors are clustered by firm.

Figure A.10: Placebo Test: non-U.S. Producer Profits

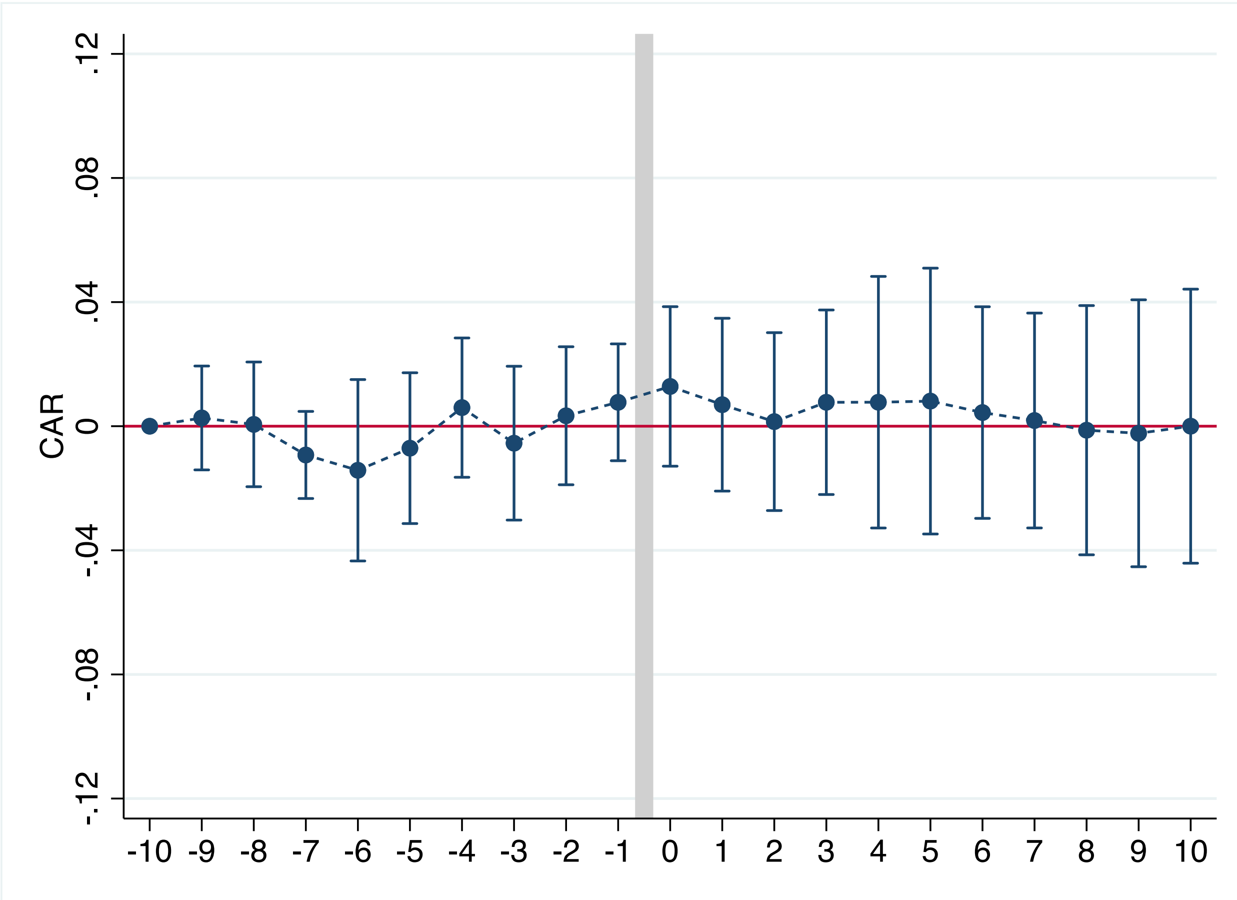


This figure shows placebo estimates of the effect of centralized futures markets on firms' operating profits scaled by total assets (*Profit*) obtained from a difference-in-differences analysis around U.S. futures introductions in a sample of non-U.S. steel producers. Specifically, the figure shows the estimated β_τ coefficients and 95% confidence intervals from the following regression:

$$Profit_{k,i,q} = \sum_{\tau=-5}^{5} \left(\beta_\tau Futures_{firm,k,i} + \theta'_\tau.X_{k,i}\right) \mathbb{1}\left\{q = \tau\right\} + \alpha_{k,i} + \alpha_{k,c,j,q} + \varepsilon_{k,i,q}.$$

Futures introductions (HRC, BUS) are indexed by k, and firms, headquarter countries, 3-digit NAICS industries, and year-quarters by i, c, j, and q. I combine quarters $q \leqslant -5$ and $q \geqslant 5$ to one dummy respectively and use the last quarter before futures trading started as the reference date, omitting $\mathbb{1}\left\{q = -1\right\}$. The sample consists of non-U.S. producers, operating in countries without steel futures introduction during the sample period (excluding China, India, South Korea, Turkey, the UAE, and the Black Sea region). $Futures_{firm}$ is an indicator equal to one for firms selling hot-rolled coil (HRC) around the 2008 introduction of HRC futures and for firms selling ferrous scrap around the 2012 introduction of busheling scrap futures (BUS). Standard errors are clustered by firm.

Figure A.11: Placebo Test: non-U.S. Producer Stock Market Valuations



This figure shows placebo estimates of centralized futures markets on firms' stock market valuations (*CAR*) obtained from a difference-in-differences analysis around the arrival of news related to U.S. futures introductions in a sample of non-U.S. steel producers. Specifically, the figure shows the estimated β_τ coefficients and 95% confidence intervals from the following regression:

$$CAR_{e,i,d} = \sum_{\tau=-10}^{10} \left(\beta_\tau Futures_{firm,e,i}\right) \mathbb{1}\left\{d = \tau\right\} + \alpha_{e,i} + \alpha_{e,c,d} + \varepsilon_{e,i,d}.$$

Events are indexed by e, firms, headquarter countries, and trading days in event time by i, c, and d. I use the first day of the event window as the reference date and thus omit $\mathbb{1}\left\{d = -10\right\}$. CAR is computed adjusting for the market return. The sample consists of non-U.S. producers, operating in countries without steel futures introduction during the sample period (excluding China, India, South Korea, Turkey, the UAE, and the Black Sea region). $Futures_{firm}$ is an indicator equal to one for firms selling hot-rolled coil (HRC) on events relating to the 2008 introduction of HRC futures and for firms selling ferrous scrap on events relating to the 2012 introduction of busheling scrap futures (BUS). Standard errors are clustered by firm and trading day.

Table A.1: Correlations Between U.S. Physical Product Price Changes and Futures Price Changes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ΔUS Physical Product Price								
$\Delta\text{Futures}_{NYMEX-HRC-US}$	0.913***								
	(4.66)								
$\Delta\text{Futures}_{NYMEX-BUS-US}$		0.218***							
		(2.72)							
$\Delta\text{Futures}_{MCX-ingot-India}$			-0.045						
			(-0.33)						
$\Delta\text{Futures}_{NCDX-ingot-India}$				0.040	0.203				
				(0.36)	(1.04)				
$\Delta\text{Futures}_{DGCX-rebar-theUAE}$						-0.006			
						(-0.02)			
$\Delta\text{Futures}_{LME-billet-Turkey}$							0.095	-0.074	
							(1.30)	(-0.86)	
$\Delta\text{Futures}_{LME-billet-Korea}$									0.071
									(0.57)
Physical Product	HRC	BUS	HRC	HRC	BUS	HRC	HRC	BUS	HRC
R^2	0.177	0.075	0.012	0.002	0.032	0.000	0.019	0.015	0.016
Observations	123	117	15	115	24	62	124	44	17

This table correlates changes in U.S. hot-rolled coil (HRC) and busheling scrap (BUS) prices with changes in futures prices. Δ*US Physical Product Price* is the change in *SteelBenchmarker* U.S. physical product market prices from one publication date to the next for HRC and BUS respectively. $\Delta Futures_{NYMEX-HRC-US}$ is the change in the NYMEX U.S. Midwest HRC futures price in between two *SteelBenchmarker* price releases. Specifically, *SteelBenchmarker* prices are released every 2nd and 4th Wednesday of a month. Futures price changes are computed from the 2nd to the 3rd Friday of the same month. The other futures price changes are computed analogously. Futures price data are from Bloomberg. I restrict the HRC (BUS) sample to five years after the HRC (BUS) futures introductions. MCX HRC futures stopped trading December 2006, MCX ingot June 2009, NCDX December 2013, DGCX September 2010, LME billet Turkey June 2014, and LME billet South Korea June 2009. Robust standard errors are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table A.2: Ex-Ante Steel Price Volatility by Product Group

	(1)	(2)	(3)	(4)	(5)
	Price Volatility				
$\text{Futures}_{product-group}$	0.011				
	(0.011)				
$\mathbb{1}\{y > 2000\}$		0.032***	0.033***		
		(0.009)	(0.010)		
$\text{Futures}_{product-group} \times \mathbb{1}\{y > 2000\}$			-0.004		
			(0.019)		
$\mathbb{1}\{y > 2003\}$				0.044***	0.045***
				(0.011)	(0.014)
$\text{Futures}_{product-group} \times \mathbb{1}\{y > 2003\}$					-0.002
					(0.025)
Product Group FE	No	Yes	Yes	Yes	Yes
R^2	0.009	0.406	0.406	0.432	0.432
Observations	126	126	126	126	126

This table presents estimates of the volatility of steel product prices before the arrival of the NYMEX steel futures. *Price Volatility* is the annual standard deviation of the monthly log price index of 6 steel product groups from the BLS Producer Price Index Series measured over the period 1987–2007. The product groups are "Hot rolled steel sheet and strip", "Cold rolled steel sheet and strip", "Hot rolled steel bars, plates, and structural shape", "Heavy melting scrap", "Shredded carbon steel scrap", "Other carbon steel scrap". $\textit{Futures}_{product-group}$ is an indicator equal to one for "Hot rolled steel sheet and strip" (HRC) and "Other carbon steel scrap" (BUS). $\mathbb{1}\{y > 2000\}$ and $\mathbb{1}\{y > 2003\}$ are indicator variables for years after 2000 and 2003, respectively. Robust standard errors are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table A.3: Ex-Ante Steel Price Cyclicality by Product Group

	(1)	(2)	(3)	(4)	(5)
	Ln(Price Index)				
Ln(US GDP)	0.423***				
	(0.142)				
Ln(US GDP) × $\text{Futures}_{product-group}$	-0.026				
	(0.077)				
Ln(Automotive)		0.394**			
		(0.168)			
Ln(Automotive) × $\text{Futures}_{product-group}$		0.004			
		(0.078)			
Ln(Construction)			0.429***		
			(0.136)		
Ln(Construction) × $\text{Futures}_{product-group}$			-0.060		
			(0.066)		
Ln(Machinery)				0.575***	
				(0.194)	
Ln(Machinery) × $\text{Futures}_{product-group}$				-0.014	
				(0.111)	
Ln(Appliances)					0.635**
					(0.293)
Ln(Appliances) × $\text{Futures}_{product-group}$					0.026
					(0.140)
Product Group FE	Yes	Yes	Yes	Yes	Yes
R^2	0.609	0.549	0.612	0.603	0.549
Observations	132	132	132	132	132

This table presents estimates of the cyclicality of steel product prices before the arrival of the NYMEX steel futures. *Ln(Price Index)* is the log price index of 6 steel product groups from the BLS Producer Price Index Series measured over the period 1986–2007. The product groups are "Hot rolled steel sheet and strip", "Cold rolled steel sheet and strip", "Hot rolled steel bars, plates, and structural shape", "Heavy melting scrap", "Shredded carbon steel scrap", "Other carbon steel scrap". $\textit{Futures}_{product-group}$ is an indicator equal to one for "Hot rolled steel sheet and strip" (HRC) and "Other carbon steel scrap" (BUS). Annual GDP data along with automotive, construction, machinery, and appliances sector output are from the BEA. Standard errors clustered by year are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table A.4: Alternative Clustering Choices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	SD(Price)	CV(Price)	Hedge (1/0)	Market Share	Ln(Price)	Profit	CAR
Baseline Coefficient	-38.636	-0.057	0.215	0.073	-0.036	-0.019	-0.049
Baseline S.E.	(6.481)***	(0.009)***	(0.096)**	(0.020)***	(0.004)***	(0.004)***	(0.010)***
Cluster Product + Date	(15.710)**	(0.030)*			(0.005)***		
Cluster Firm + Date			(0.086)**	(0.014)***		(0.005)***	(0.014)**
Cluster Product Group			(0.079)***	(0.021)***		(0.005)***	(0.011)***
Cluster Product Group + Date			(0.076)***	(0.022)***		(0.005)***	(0.015)**
Product FE	Yes	Yes	No	No	Yes	No	No
Publication Date FE	Yes	Yes	No	No	Yes	No	No
Firm FE	No	No	Yes	Yes	No	Yes	Yes
Industry $\times$ Year FE	No	No	Yes	No	No	No	No
Controls $\times$ Year FE	No	No	Yes	No	No	No	No
Industry $\times$ Year-Quarter FE	No	No	No	Yes	No	Yes	No
Controls $\times$ Year-Quarter FE	No	No	No	Yes	No	Yes	No
Event Date FE	No	No	No	No	No	No	Yes
R^2	0.769	0.676	0.701	0.981	0.917	0.629	0.257
Observations	708	708	2,993	1,419	19,653	5,095	1,106

This table presents the baseline results of the effect of centralized futures markets on price dispersion, commodity hedging, cost-sensitivity of market share, prices, profits, and valuations obtained from difference-in-differences analyses around futures introductions along with the standard errors of alternative clustering choices. Product groups are formed based on product similarity in annual reports. Firms are grouped based on the fixed industry classification with 300 industries developed in Hoberg and Phillips (2010, 2016). This grouping of firms yields 82, 44, 82, and 80 clusters in Columns (3), (4), (6), and (7), respectively. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table A.5: Dynamics Relative to Pre-Period Average

	(1)	(2)	(3)	(4)	(5)
	CV(Price)	Hedge (1/0)	Ln(Price)	Profit	$\text{CAR}_{-2,+2}$
Futures $\times\ \mathbb{1}\{t \leqslant -5\}$	-0.030		0.007	0.005	-0.003
	(0.020)		(0.010)	(0.004)	(0.005)
Futures $\times\ \mathbb{1}\{t = -4\}$	0.056	0.030	-0.017	-0.005	0.009
	(0.045)	(0.099)	(0.028)	(0.004)	(0.010)
Futures $\times\ \mathbb{1}\{t = -3\}$	0.006	0.010	0.010	-0.003	0.008
	(0.046)	(0.095)	(0.017)	(0.003)	(0.009)
Futures $\times\ \mathbb{1}\{t = -2\}$	-0.043	-0.016	-0.000	0.001	-0.007
	(0.046)	(0.078)	(0.015)	(0.002)	(0.011)
Futures $\times\ \mathbb{1}\{t = -1\}$	0.011	-0.023	-0.000	0.000	-0.007
	(0.028)	(0.079)	(0.023)	(0.004)	(0.010)
Futures $\times\ \mathbb{1}\{t = 0\}$	-0.091***	0.156	-0.015	-0.018**	-0.017*
	(0.025)	(0.107)	(0.023)	(0.009)	(0.010)
Futures $\times\ \mathbb{1}\{t = 1\}$	-0.099***	0.244**	-0.047**	-0.021***	-0.015***
	(0.038)	(0.096)	(0.020)	(0.007)	(0.006)
Futures $\times\ \mathbb{1}\{t = 2\}$	-0.138***	0.243**	-0.038**	-0.019**	-0.024***
	(0.020)	(0.097)	(0.015)	(0.008)	(0.008)
Futures $\times\ \mathbb{1}\{t = 3\}$	-0.106***	0.224**	-0.061***	-0.024***	-0.019*
	(0.021)	(0.098)	(0.021)	(0.006)	(0.009)
Futures $\times\ \mathbb{1}\{t = 4\}$	-0.093***	0.253**	-0.046**	-0.018***	-0.025**
	(0.027)	(0.116)	(0.020)	(0.005)	(0.010)
Futures $\times\ \mathbb{1}\{t \geqslant 5\}$	-0.081***		-0.028***	-0.019***	-0.053***
	(0.020)		(0.010)	(0.005)	(0.007)
Product FE	Yes	No	Yes	No	No
Time FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	Yes
Controls $\times$ Time FE	No	Yes	No	Yes	No
Observations	708	2,994	19,653	4,877	23,274

This table presents dynamic effects. Columns (1) and (3) estimate product-level specifications akin to Figures 2 and 4, Column (2) and (4) estimate firm-level specifications akin to Figures 3 and 5, and Column (5) estimates an event study specification akin to Figure 6. Instead of omitting a single point in time, I constrain the coefficients in the pre-period to average to zero, following the procedure described in Miller (2023). *Futures* refers to the $Futures_{product}$ indicator in Columns (1) and (3), and to the $Futures_{firm}$ indicator in Columns (2), (4), and (5). Time t refers to publication dates in Columns (1) and (3), to years in Column (2), to year-quarters in Column (4), and to trading days in Column (5). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table A.6: Balance on Observables

	(1)	(2)	(3)
Dependent Variable:	Coefficient	Standard Error	Observations
Ln(Assets)$_{q=-1}$	1.684	0.478	355
Firm Age$_{q=-1}$	-9.285	5.982	355
Sales Growth$_{q=-1}$	0.014	0.044	355
$\beta_{sales,gdp}$	0.614	0.873	342
$\beta_{sales,auto}$	-0.153	0.361	342
$\beta_{sales,construction}$	-0.356	0.374	342
$\beta_{sales,machines}$	-0.183	0.366	342
$\beta_{sales,appliances}$	0.208	0.450	342
$\beta_{profit,iron/scrap}$	-0.032	0.024	342
$\beta_{cogs,iron/scrap}$	-0.042	0.062	342
Share International Sales$_{q=-1}$	-0.040	0.069	355
Share Main Industry Sales$_{q=-1}$	-0.069	0.066	355

This table shows the coefficient estimates and corresponding standard errors as well as the number of observations from regressions of the following form: $Y_{k,i} = \alpha_{k,j} + \beta.\mathit{Futures}_{firm,k,i} + \varepsilon_{k,i}$. Futures introductions (HRC, BUS) are indexed by k, firms by i, and industries by j. $Y_{k,i}$ is the dependent variable of interest for firm i and futures introduction k, measured as of quarter $q = -1$ (the last quarter before the futures commenced trading). $\mathit{Futures}_{firm,k,i}$ is the treatment indicator for firm i around futures introduction k. $\alpha_{k,j}$ is an introduction specific 3-digit NAICS industry fixed effect. Standard errors are clustered by firm.

Table A.7: Producer Profit Sensitivity to Steel Prices

	(1)	(2)	(3)
	$\Delta\beta_{profit,steel}$		
Futures_{firm}	-0.034**	-0.039**	-0.040**
	(0.017)	(0.018)	(0.019)
Introduction FE	Yes	Yes	Yes
Industry FE	No	Yes	Yes
Controls	No	No	Yes
R^2	0.023	0.035	0.050
Observations	304	304	304

This table presents estimates of the effect of centralized futures markets on producer profit sensitivity to steel prices ($\Delta\beta_{profit,steel}$) obtained from a difference-in-differences analysis around futures introductions. $\Delta\beta_{profit,steel}$ is the change in the sensitivity of profits to steel prices from the pre ($q = -7$ to $q = -1$) to the post ($q = 1$ to $q = 7$) period. $\beta_{profit,steel}$ is estimated for the pre and post period separately by regressing *Profit* on the year-on-year change in steel prices for each firm. *Futures*$_{firm}$ is an indicator equal to one for firms selling hot-rolled coil (HRC) around the 2008 introduction of HRC futures and for firms selling ferrous scrap around the 2012 introduction of busheling scrap futures (BUS). Controls are measured in $q = -1$ and include the log of assets, firm age and sales growth. Standard errors clustered by firm are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table A.8: Physical Product Market Quantities - DiD Estimation Around Futures Introductions

	(1)	(2)	(3)
	Ln(Tons)		
Post×Futures$_{product}$	0.012	0.020	0.005
	(0.048)	(0.067)	(0.070)
Product FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Sample	All	HRC	BUS
R^2	0.975	0.980	0.972
Observations	81	27	54

This table presents estimates of the effect of centralized futures markets on physical product market quantities (*Ln(Tons)*) obtained from a difference-in-differences analysis around futures introductions. *Futures$_{product}$* is an indicator equal to one for hot-rolled coils (HRC) around the 2008 introduction of HRC futures and for busheling scrap (BUS) around the 2012 introduction of BUS futures. *Post* is an indicator equal to one for the years $y = 0, 1, \ldots, 4$, where $y = -1$ denotes the last year before the futures started trading. Column (2) reports the results using only the HRC introduction while Column (3) reports the results using only the BUS introduction. Data on steel production in metric tons for hot rolled sheet and control steel products (cold rolled sheet, plate) and ferrous scrap consumption in metric tons for busheling scrap and control scrap products (shredded scrap, heavy melting scrap) are from the U.S. Geological Survey, Iron and Steel (Scrap) Statistics. The HRC sample spans the period 2004 to 2012 and uses data on hot rolled sheet, cold rolled sheet, and plate production in metric tons. The BUS sample spans the period 2008 to 2016 and uses data on hot rolled sheet, cold rolled sheet, and plate production in metric tons along with data on ferrous scrap consumption in metric tons for busheling scrap, shredded scrap, and heavy melting scrap. Robust standard errors are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table A.9: Alternative Measures of Producer Profits

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Profit Measure						
	EBITDA	EBIT	EBT	NI	CI	EBITDA	EBITDA
	AT_{q-1}	AT_{q-1}	AT_{q-1}	AT_{q-1}	AT_{q-1}	AT_{pre}	$Sales_q$
Post×$Futures_{firm}$	-0.019***	-0.019***	-0.020***	-0.015***	-0.015***	-0.015***	-0.036***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.011)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry×YQ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.629	0.636	0.661	0.465	0.447	0.640	0.755
Observations	5,095	5,095	5,095	5,095	5,095	5,095	5,095

This table presents estimates of the effect of centralized futures markets on producers' profits obtained from a difference-in-differences analysis around futures introductions using alternative measures of profits. Column (1) shows the baseline estimate of operating profits before depreciation (EBITDA) scaled by lagged assets (AT_{q-1}) as shown in Column (2) of Table 6. Columns (2) to (5) use operating profits after depreciation (EBIT), earnings before taxes (EBT), net income (NI), and comprehensive income (CI) as numerator instead, all scaled by lagged assets. Column (6) scales EBITDA by assets in the last period before futures trading (AT_{pre}), while Column (7) scales EBITDA by contemporaneous sales ($Sales_q$). *Futures*$_{firm}$ is an indicator equal to one for firms selling hot-rolled coil (HRC) around the 2008 introduction of HRC futures and for firms selling ferrous scrap around the 2012 introduction of busheling scrap futures (BUS). *Post* is an indicator equal to one in the quarters $q = 0, 1, \ldots, 7$, where $q = -1$ denotes the last quarter before the futures started trading. All columns include the baseline controls (log of assets, firm age, and sales growth, measured in $q = -1$ and interacted with the time fixed effects). Standard errors clustered by firm are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table A.10: Event Study - Split by Ex-Ante Commodity Derivatives Usage

	(1)	(2)	(3)	(4)
	$\text{CAR}_{-2,+2}$			
	Derivatives Usage		Derivatives Propensity	
	Low	High	Low	High
Futures_{firm}	-0.042***	-0.047***	-0.047***	-0.042***
	(0.013)	(0.011)	(0.015)	(0.009)
Firm FE	Yes	Yes	Yes	Yes
Event Date FE	Yes	Yes	Yes	Yes
R^2	0.233	0.335	0.250	0.286
Observations	693	342	590	516

This table presents sample splits of the event study results shown in Column (1) of Table 7. Column (1) and (2) split the sample based on a dummy variable (*Hedge (1/0)*) equal to one for producers' discussing commodity derivative usage in their annual report. Column (3) and (4) estimates the propensity to discuss commodity derivative usage based on observable firm characteristics and splits the sample at the median. Both variables are measured in the pre-period from 2004 to 2007. Propensity to discuss commodity derivatives is estimated using firms' size, age, sales growth, tangibility, leverage and 3-digit NAICS industry. Tangibility is measured by PPE and leverage by the sum of long and short-term debt, both scaled by lagged assets. (*CAR*) is the cumulative abnormal return during the five-day window around news increasing the likelihood of hot-rolled coil (HRC) and busheling scrap (BUS) futures. $\textit{Futures}_{firm}$ is equal to one for HRC (ferrous scrap) selling firms for news relating to the HRC (BUS) introduction. Standard errors clustered by firm are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table A.11: Summary Statistics - Additional Controls

	(1)	(2)	(3)	(4)	(5)	(6)
Variable:	Obs.	Mean	SD	$p1$	$p50$	$p99$
$\beta_{sales,gdp}$	342	2.594	3.138	-7.195	2.477	11.997
$\beta_{sales,auto}$	342	0.456	1.265	-2.427	0.315	5.483
$\beta_{sales,construction}$	342	0.909	1.342	-3.091	0.872	5.077
$\beta_{sales,machines}$	342	1.009	1.321	-2.876	0.937	4.597
$\beta_{sales,appliances}$	342	0.859	1.657	-3.087	0.720	5.229
$\beta_{profit,iron/scrap}$	342	0.032	0.085	-0.230	0.033	0.276
$\beta_{cogs,iron/scrap}$	342	0.104	0.221	-0.416	0.105	0.731
Import Penetration	355	0.115	0.213	0.000	0.011	0.803
Import Penetration$_{cij}$	355	0.017	0.025	0.000	0.003	0.105
Share International Sales	355	0.216	0.246	0.000	0.137	1.000
Share Main Industry Sales	355	0.850	0.234	0.000	1.000	1.000
Acquisition (1/0)	355	0.068	0.251	0.000	0.000	1.000

This table presents summary statistics for the additional controls. Internet Appendix C.5 provides definitions.

Table A.12: Import Competition Around HRC Futures Introduction

	(1)	(2)	(3)	(4)	(5)
	Import Penetration				
Post×Futures$_{product}$	-0.011				
	(0.024)				
Post×Futures$_{industry}$		-0.030	-0.009	-0.022	-0.016
		(0.040)	(0.007)	(0.035)	(0.011)
Countries of Origin	All	All	NAFTA	Ex. NAFTA	CIJ
Product FE	Yes	No	No	No	No
Industry FE	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.856	0.910	0.887	0.915	0.885
Observations	27	117	117	117	117

This table presents estimates of the relationship between centralized futures markets and import competition around the 2008 introduction of HRC futures. *Futures*$_{product}$ is an indicator equal to one for hot-rolled coil, while *Futures*$_{industry}$ is an indicator equal to one for the hot-rolled coil (HRC) producing industry (NAICS 3311). *Post* is an indicator equal to one in the years $y = 0, 1, \ldots, 4$, where $y = -1$ denotes the last year before the futures started trading. Column (1) relies on product-level import data and measures import penetration as quantities (metric tons) imported in year t, scaled by initial market absorbtion in the first year of the sample ($y = 2004$). Market absorption is defined as output plus imports less exports. Column (2)-(4) rely on industry-level import data, allowing to break down imports by country of origin. Import penetration is measured as imports in year t, scaled by initial industry employment. Column (1) and (2) consider import competition from all countries, Column (3) from NAFTA countries, Column (4) from countries outside NAFTA, and Column (5) from the largest steel producing countries China, India, and Japan. The product sample is restricted to steel mill products around the HRC introduction, since the breakdown of ferrous scrap imports is not granular enough to identify busheling scrap. The industry sample is restricted to manufacturing industries around the HRC introduction since the industry import data does not cover non-manufacturing industries. Robust standard errors are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table A.13: Robustness - Other Firm-Level Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	Hedge (1/0)					
Post×Futures$_{firm}$	0.258***	0.229**	0.236**	0.257***	0.249***	0.254***
	(0.089)	(0.093)	(0.107)	(0.090)	(0.092)	(0.086)
R^2	0.689	0.701	0.706	0.690	0.694	0.695
Observations	2,993	2,927	2,922	2,993	2,993	2,749
Panel B:	Market Share					
Post×Futures$_{firm}$×EAF×Iron/Scrap	0.054***	0.070**	0.063***	0.046**	0.060***	0.068***
	(0.016)	(0.027)	(0.022)	(0.020)	(0.019)	(0.017)
R^2	0.980	0.980	0.980	0.980	0.980	0.980
Observations	1,419	1,370	1,359	1,419	1,419	1,327
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Business Cycle Controls	No	Yes	No	No	No	No
Iron/Scrap Price Controls	No	No	Yes	No	No	No
Import Controls	No	No	No	Yes	No	No
Segment Controls	No	No	No	No	Yes	No
Excluding M&A	No	No	No	No	No	Yes

This table presents robustness tests for the hedging (Panel A) and market share (Panel B) results. Column (1) shows the baseline results presented in Column (1) of Tables 3 and 4. Column (2) adds business cycle controls (firms' sales beta with respect to aggregate GDP, automotive, construction, machinery, and appliance sector growth all interacted with the time fixed effects), Column (3) adds controls for iron ore and scrap prices (firms' profit and input cost beta with respect to iron ore relative to scrap prices and a dummy for *EAF* producers, all interacted with the time fixed effects, as well as interactions of the *Futures*$_{firm}$ dummy with the ratio of iron ore to scrap prices and with the log of iron ore prices), Column (4) adds import competition controls (the *Futures*$_{firm}$ dummy interacted with industry-level import competition from all countries and from China, India, and Japan), and Column (5) adds segment controls (the share of foreign sales and the share of sales in the main industry interacted with time fixed effects). Column (6) excludes observations involved in M&A activity. *Futures*$_{firm}$ is an indicator equal to one for firms selling hot-rolled coil (HRC) around the 2008 introduction of HRC futures and for firms selling ferrous scrap around the 2012 introduction of busheling scrap futures (BUS). *Post* is an indicator equal to one after the HRC and BUS futures started trading. *EAF* is an indicator equal to one for electric arc furnace (EAF) producers. EAF producers use steel scrap as their primary raw material whereas basic oxygen furnace (BOF) producers use primarily iron ore. *Iron/Scrap* is the quarterly ratio of iron ore to scrap prices. Panel A is at the yearly frequency, while Panel B is at the quarterly frequency. Time fixed effects are defined accordingly. The sample in Panel B is restricted to the HRC introduction. Standard errors clustered by firm are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table A.14: Robustness - Event Study Excluding Event Dates with Low Market Returns

	(1)	(2)	(3)	(4)
	$\text{CAR}_{-2,+2}$			
Futures_{firm}	-0.059***	-0.040***	-0.041***	-0.042***
	(0.016)	(0.013)	(0.014)	(0.014)
Firm FE	Yes	Yes	Yes	Yes
Event Date FE	Yes	Yes	Yes	Yes
Model	m	mm	ff	ffm
R^2	0.355	0.336	0.319	0.319
Observations	612	612	612	612

This table presents OLS estimates of producers' cumulative abnormal returns (*CAR*) during the five-day window around news increasing the likelihood of hot-rolled coil (HRC) and busheling scrap (BUS) futures. The estimates are based on regressions of *CAR* on the $\textit{Futures}_{firm}$ indicator, excluding event dates with market return below the median weekly market return for that year. Market return is defined as the return on the value-weighted market portfolio, including all distributions (CRSP item *vwretd*). $\textit{Futures}_{firm}$ is an indicator equal to one for firms selling hot-rolled coil (HRC) on events relating to the 2008 introduction of HRC futures and for firms selling ferrous scrap on events relating to the 2012 introduction of busheling scrap futures (BUS). Standard errors clustered by firm are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table A.15: Placebo Test - Control Steel Products

	(1)	(2)	(3)	(4)
Panel A:	Futures_{firm}	Placebo_{firm}	Difference	Standard Error
$\beta_{sales,gdp}$	3.531	3.796	-0.266	0.760
$\beta_{sales,auto}$	0.297	0.411	-0.115	0.256
$\beta_{sales,construction}$	0.810	1.301	-0.491	0.296
$\beta_{sales,machines}$	0.997	1.543	-0.546	0.337
$\beta_{sales,appliances}$	1.226	0.826	0.399	0.406
Panel B:	Hedge (1/0)	Market Share	Profit	$\text{CAR}_{-2,+2}$
Post$\times$$\text{Placebo}_{firm}$	0.091		-0.005	
	(0.056)		(0.004)	
Post$\times$$\text{Placebo}_{firm}$$\times$EAF$\times$Iron/Scrap		-0.022		
		(0.022)		
Placebo_{firm}				-0.006
				(0.007)
Firm FE	Yes	Yes	Yes	No
Year FE	Yes	No	No	No
Year-Quarter FE	No	Yes	Yes	No
Interactions	No	Yes	No	No
Event Date FE	No	No	No	Yes
R^2	0.676	0.980	0.610	0.025
Observations	2,758	1,314	4,696	984

This table shows placebo tests within the U.S. firm sample. Panel A compares the sensitivity of firms' sales growth to overall economic conditions and key steel consuming sectors (automotive, construction, machinery, appliances) for firms selling treated (*Futures*$_{firm}$) and control products (*Placebo*$_{firm}$). Column (1) shows the mean sensitivity for treated firms, Column (2) shows the mean sensitivity for placebo firms, Column (3) shows the difference between Columns (1) and (2), and Column (4) the standard error of the difference shown in Column (3). *Futures*$_{firm}$ is an indicator equal to one for HRC and BUS selling firms. *Placebo*$_{firm}$ is an indicator equal to one for firms selling one of the control products from the product-level tests (cold rolled coil, plate, heavy melting scrap, shredded scrap). Panel B presents placebo tests in the sample of U.S. producers, excluding firms selling the treated products. Columns (1) to (4) estimate the specifications shown in Column (1) of Tables 3, 4, 6, and 7. *Post* is an indicator equal to one after the HRC and BUS futures started trading. *EAF* is an indicator equal to one for electric arc furnace (EAF) producers. EAF producers use steel scrap as their primary raw material whereas basic oxygen furnace (BOF) producers use primarily iron ore. *Iron/Scrap* is the quarterly ratio of iron ore to scrap prices. The sample in Column (2) is restricted to the HRC introduction. Standard errors clustered by firm are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

B Information in Annual Reports

B.1 Treatment Status

To identify firms selling the treated products, I exploit information contained in firms' annual reports. For the HRC introduction, I start with firms operating in 4-digit NAICS industry 3311 (Iron and Steel Mills and Ferroalloy Manufacturing) that mention "hot coil", "hot band", or "hot sheet" in their annual report from the beginning of the sample period until 2008. For the BUS futures introduction, I start with firms mentioning either "ferrous scrap business", "steel scrap business", "ferrous recyling business", or "steel recyling business" from the beginning of the sample period until 2012. I then manually identify firms selling HRC and ferrous scrap using the last annual report prior to the onset of treatment. In particular, I do not consider firms treated that purchase rather than sell the treated products.

B.2 Commodity Hedging

To identify firms which use commodity derivatives to hedge, I follow the methodology and list of keywords proposed in Almeida, Hankins, and Williams (2017) and classify firms as commodity hedger in a given year if they mention commodity hedging related keywords in their annual report. The list of keywords is "hedge fuel", "fuel hedge", "fuel call option", "commodity derivative", "commodity contract", "commodity forward", "commodity future", "commodity hedge", "commodity hedging", "commodity option", "commodity swap", "hedges of commodity price", "uses derivative financial instruments to manage the price risk", "uses financial instruments to manage the price risk", "uses derivative financial instruments to manage price risk", "uses derivatives to manage the price risk", "uses derivatives to manage price risk", "forward contracts for certain commodities", "forward contracts for commodities", "derivatives to mitigate commodity price risk", "futures to mitigate commodity price risk", "options to mitigate commodity price risk", "swaps to mitigate commodity price risk", "corn future", "cattle future", or "commodity price swap". I obtain similar results following Pérez-González and Yun (2013) and using the following keywords instead: "commodity derivatives", "commodity futures", "commodity forwards", "commodity options", "commodity swaps", or "commodity hedging".

B.3 Sample Definition

I restrict the sample to firms in 3-digit NAICS industries 331 (Primary Metal Manufacturing), 332 (Fabricated Metal Product Manufacturing), and 423 (Merchant Wholesalers, Durable Goods). I add firms to the sample if they mention operating a ferrous scrap recycling business in their annual report in the years up to 2012 even if their 3-digit NAICS industry is outside 331, 332, and 423. I use historical NAICS codes from the beginning of the sample period from Compustat Northamerica Fundamentals Annual. If the historical NAICS code is not available in the first year of the sample period I use the earliest available historical NAICS code.

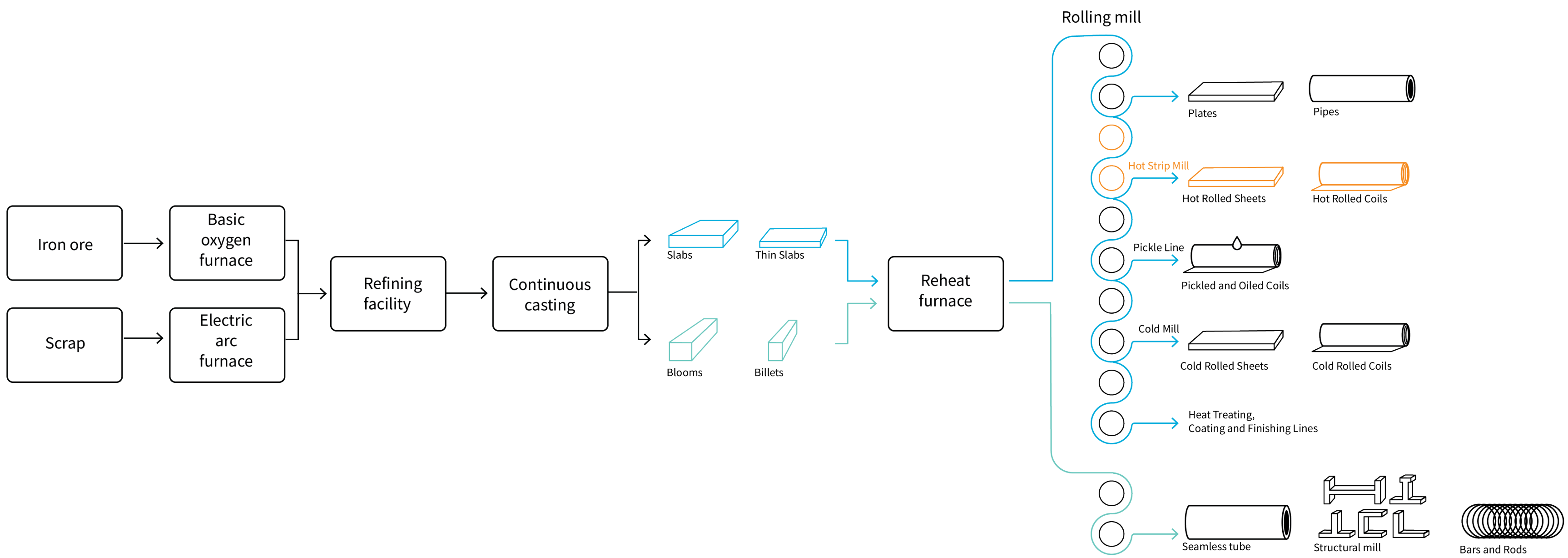
B.4 Production Technology

To identify electric arc furnace (EAF) producers, I search for the keywords "electric arc", "integrated producer", and "basic oxygen furnace" in firms' annual reports from the beginning of the sample period until 2008.[47] I classify firms as electric arc producers if they operate in NAICS industry 3311 and mention "electric arc" more frequently then "integrated producer" or "basic oxygen furnace". I verify the production technology using the last annual report prior to the HRC futures trading start.

[47] Basic oxygen furnace (BOF) producers are typically also referred to as integrated producers.

C Supplemental Material

C.1 Steel Production Process



This figure shows the production process of steel. Steel is made either from iron ore, using basic oxygen furnaces (BOF), or from steel scrap, using electric arc furnaces (EAF). After refining, raw steel is cast into semifinished products (slabs, thin slabs, blooms, billets), which are then reheated and further processed in rolling mills. Slabs and thin slabs are processed into plate, pipe, hot-rolled sheets and coils, pickled and oiled coils, cold-rolled sheets and coils, as well as heat-treated and coated sheets and coils. Blooms and billets are processed into seamless tube, structural mill products, as well as bars and rods. Source: Based on American Steel and Iron Institute.

C.2 Steel Futures Around the Globe

Introduction Year	**Exchange**	**Target Region**	**Product**
2004	MCX	India	Pencil Ingots
2004	MCX	India	HRC
2005	NCDX	India	Mild-steel ingots
2007	DGCX	the UAE	Rebar
2008	LME	Turkey	Billet
2008	LME	South Korea	Billet
2008	**NYMEX**	**USA**	**Hot-rolled coils**
2009	SHFE	China	Wire rod
2009	SHFE	China	Rebar
2011	NYMEX	Black Sea	Billet
2012	NYMEX	China	Rebar
2012	**NYMEX**	**USA**	**Busheling scrap**
2014	SHFE	China	Hot-rolled coils
2015	LME	Turkey	Heavy-melting scrap
2015	LME	Turkey	Rebar

This table lists the futures contracts introduced globally for steel products during the sample period. Column (1) presents the year of the introduction, Column (2) the exchange, Column (3) the geographic region targeted by the futures, and Column (4) the underlying steel product.

C.3 Event Study Dates

Date	Event	Product
23.07.2007	Contract signed between World Steel Dynamics and NYMEX to launch a hot-rolled coil (HRC) futures contract settled against SteelBenchmarker reference prices. Source: American Metal Market.	HRC
01.11.2007	CME plans revealed to launch an HRC futures contract settled against price index developed by CRU International. Source: American Metal Market.	HRC
24.06.2008	CME/NYMEX plans revealed to launch an HRC futures contract settled against price index developed by CRU International in fall. Source: American Metal Market.	HRC
04.08.2008	Official announcement that CME/NYMEX HRC contract will be settled against price index developed by CRU International. Source: Financial Times, NYMEX press release.	HRC
24.09.2008	Official announcement that CME/NYMEX HRC contract will start trading end of October 2008. Source: CME Group press release.	HRC
15.06.2012	CME Group licenses American Metal Market's midwest ferrous scrap index. Source: American Metal Market.	BUS
17.08.2012	Official announcement of CME/NYMEX to launch U.S. midwest busheling scrap (BUS) futures. Source: American Metal Market, CME Group press release.	BUS

C.4 Media Coverage

Quote	Source
In a move to bring clarity to a **big-but-opaque market** that has been rocked in recent months by unexpected price increases, **some groups are considering establishing futures markets and indexes that track the price of steel**. Dow Jones & Co., publisher of The Wall Street Journal, is considering launching a monthly price-per-ton index for benchmark **hot-rolled and cold-rolled** steel products sold in the U.S. in coming weeks and charging about $500 a year for subscriptions. [...] **Indexes and futures markets could add transparency to prices** and smooth out fluctuations. Unlike many other commodities that are traded in public markets, **steel is bought and sold in private transactions, and manufacturers pay different steel prices** based on their size and their relationships with steel makers and suppliers. What a company pays for steel can be a closely guarded secret.	Wall Street Journal, 01.04.2004
"People think it would be disruptive to the pricing," he (John Surma, CEO U.S. Steel) said. [...] Many steel buyers rely on trade publications, analyst reports, and networking to determine what steel companies are charging for prices and adjust their buying patterns accordingly. [...] John Hitchcock, a managing director at Dow Jones, said the index would be based on monthly transaction data regularly submitted by a large group of buyers and sellers, rather than just price surveys of steel buyers as is commonly practiced by analysts and industry publications. Dow Jones is considering in return offering discounts to data providers. Klaus Abstoss [...] said a futures market would be hard to adopt. **"Transparency is very difficult in this industry."**	Wall Street Journal, 01.04.2004
That is why Nucor Corp. chairman, president and chief executive officer Dan DiMicco says **steel futures will allow the financial markets to set steel prices rather than steel mills.**	American Metal Market, 28.06.2007
Futures contracts bring **pricing transparency to the steel market.**	John Conheeney, ICAP, Platts, 16.09.2008
The major mills have a dominance in pricing in the current system, and they're happy not to introduce any **new means of price discovery.**	Paul Shellman, CME Group, American Metal Market, 17.10.2008.
Knowledge is power - knowing more than the other side of the table is a huge advantage in any negotiation, particularly in the steel business where prices are not controlled by a public auction (like most other metals are). **So what factors do I suggest a buyer look at to assist in predicting the future price of steel? Item number one is the futures price of steel. After all there are many millions of dollars being bet on these prices and representing the sum of the markets overall judgement of what is going to happen next.** Steel Market Update publishes the CME HRC Forward Curve at the bottom of its home page.	Steel Market Update, extracted 17.03.2017 from `steelmarketupdate.com`

C.5 Variable Definitions

Variable	Definition
Acquisition (1/0)	Indicator variable equal to one for observations with the absolute value of acquistions greater than 5% of assets (atq). Quarterly acquistions are computed from year-to-date acquisitions (aqcy). Source: Compustat.
$\beta_{cogs,iron/scrap}$	Firms' cost-of-goods-sold (COGS) beta with respect to iron ore relative to scrap prices, estimated by regressing COGS growth on iron ore-to-scrap price changes using annual data in the 20 years before the respective introduction. Source: Compustat, BLS.
$\beta_{profit,iron/scrap}$	Firms' profit beta with respect to iron ore relative to scrap prices, estimated by regressing profit (oibdp), scaled by beginning-of-period total assets (at), on iron ore-to-scrap price changes using annual data in the 20 years before the respective introduction. Source: Compustat, BLS.
$\beta_{sales,appliances}$	Firms' sales beta with respect to the household appliance industry (NAICS 3352), estimated by regressing sales growth on household appliance industry sales growth using annual data in the 20 years before the respective introduction. Source: Compustat, NBER-CES.
$\beta_{sales,auto}$	Firms' sales beta with respect to the automotive industry (NAICS 3361, 3362, 3363), estimated by regressing sales growth on automotive industry sales growth using annual data in the 20 years before the respective introduction. Source: Compustat, NBER-CES.
$\beta_{sales,construction}$	Firms' sales beta with respect to the construction sector (NAICS 23), estimated by regressing sales growth on construction output growth using annual data in the 20 years before the respective introduction. Source: Compustat, BEA.
$\beta_{sales,GDP}$	Firms' sales beta with respect to GDP, estimated by regressing sales growth on GDP growth using annual data in the 20 years before the respective introduction. Source: Compustat, BEA.
$\beta_{sales,machines}$	Firms' sales beta with respect to machinery manufacturing (NAICS 333), estimated by regressing sales growth on machinery manufacturing industry sales growth using annual data in the 20 years before the respective introduction. Source: Compustat, BEA.
CAR	Cumulative abnormal return using either the market-adjusted model (*market-adj.*), the CAPM (*CAPM*), the Fama-French three factor model (*3-factor*), or Carhart four factor model (*4-factor*). Source: WRDS U.S. Daily Event Study.
CV(Price)	Coefficient of variation of physical product market prices, computed as the standard deviation across different price providers for a given product and publication date, scaled by the corresponding average price for that product and publication date. Source: SteelBenchmarker.
$\Delta\beta_{profit,steel}$	Change in the sensitivity of profits to steel prices from the pre ($q = -7$ to $q = -1$) to the post ($q = 1$ to $q = 7$) period. $\beta_{profit,steel}$ is estimated for the pre and post period separately by regressing $Profit/Assets$ on the year-on-year change in steel prices for each firm. Source: Compustat, BLS.
ΔFutures$_{e-p-r}$	Change in the futures price on exchange e, for product p, targeted at region r in between two *SteelBenchmarker* price releases. *SteelBenchmarker* prices are released every 2nd and 4th Wednesday of a month. Futures price changes are computed from the 2nd to the 3rd Friday of the same month. Source: Bloomberg.

Variable	Definition
ΔUS Physical Product Price	Change in U.S. physical product market prices from one publication date to the next for HRC and BUS respectively. Source: SteelBenchmarker.
EAF	Indicator equal to one for firms classified as electric arc furnace producers based on their annual reports between 2003 and 2008. Source: Firms' annual reports.
Firm Age	Firm age is computed as the difference between the current year and the year founded. If the year founded is missing, the first year in Compustat is taken instead. Source: Compustat, Jay Ritter's website.
Futures$_{firm}$	Indicator equal to one for firms in 4-digit NAICS industry 3311 mentioning selling hot-rolled coils (HRC) in their annual report around the 2008 introduction of HRC futures and for firms mentioning the processing of ferrous scrap in their annual reports around the 2012 introduction of busheling scrap futures (BUS). Source: Firms' annual reports, Compustat.
Futures$_{product-group}$	Indicator equal to one for product group "Hot rolled steel sheet and strip" (HRC) and "Other carbon steel scrap" (BUS). Source: BLS Producer Pirce Index Series.
Futures$_{industry}$	Indicator equal to one for 4-digit NAICS industry 3311 around HRC futures introduction. Source: Peter Schott's website, NBER-CES.
Futures$_{product}$	Indicator equal to one for hot-rolled coils around the 2008 introduction of hot-rolled coil futures (HRC) and busheling scrap around the 2012 introduction of busheling scrap futures (BUS). Source: SteelBenchmarker.
Hedge (1/0)	Indicator variable equal to one if the firm mentions commodity derivatives in their annual report. Source: Firms' annual reports.
Import Penetration$_{industry}$	Total imports in million USD into the U.S. by 4-digit NAICS industry and year, scaled by industry employment in 2004. Source: Peter Schott's website, NBER-CES.
Import Penetration$_{product}$	Total imported quantities (in metric tons) into the U.S. by product and year, scaled by market absorption in 2004. Market absorption is defined as output plus imports less exports (all in metric tons). Source: U.S. Geological Survey - Iron and Steel Statistics.
Iron/Scrap	Quarterly ratio of iron ore to scrap price index. Source: BLS.
Ln(Assets)	Natural logarithm of total assets (atq). Source: Compustat.
Ln(US GDP)	Natural logarithm of annual U.S. GDP. Source: BEA.
Ln(Iron Ore Price Index)	Natural logarithm of quarterly iron ore price index. Source: BLS.
Ln(Price)	Natural logarithm of physical product market price. Source: SteelBenchmarker.
Ln(Price Index)	Natural logarithm of annual product group price index. Source: BLS.

Variable	Definition
Ln(Sectoral Output)	Natural logarithm of annual output for the construction, automotive (motor vehicles, bodies, trailers, and parts), machinery, and appliances (electrical equipment, appliances, and components) sector, respectively. Source: BEA.
Ln(Tons)	Natural logarithm of physical product market quantities. Quantities are measured by shipments in thousand metric tons for steel mill products (hot-rolled sheet, cold-rolled sheet, plate), and by consumption in thousand metric tons for ferrous scrap products (busheling scrap, shredded scrap, heavy melting scrap). Source: U.S. Geological Survey - Iron and Steel (Scrap) Statistics.
Market Share	Share of sales (saleq) in a given 4-digit NAICS industry and year-quarter. Source: Compustat.
Merger (1/0)	Indicator variable equal to one for firms with comparability status (compst) equal to AA, AB, AF, AR, AS, CA, CB, or CC in the years 2007, 2008, 2009, 2011, 2012, or 2013. Source: Compustat.
Placebo$_{firm}$	Indicator equal to one for firms mentioning selling cold-rolled coils or plates in their annual report and for firms mentioning the processing of heavy melting scrap or shredded scrap in their annual report. Source: Firms' annual reports, Compustat.
Profit	Operating profit (oibdpq) divided by book value of total assets (atq) at the end of the previous quarter. Source: Compustat.
Sales Growth	Quarterly sales (saleq) growth. Source: Compustat.
Sectoral Output Growth	Quarterly output growth for the construction, automotive (motor vehicles, bodies, trailers, and parts), machinery, and appliances (electrical equipment, appliances, and components) sector, respectively. Source: BEA.
SD(Price)	Standard deviation of physical product market prices, computed across different price providers for a given product and publication date. Source: SteelBenchmarker.
Share International	Sales outside the US, scaled by total geographic segment sales. Source: Compustat Segments.
Share Main Industry Sales	Sales in the firm's main industry, scaled by total business segment sales. Source: Compustat Segments.
Steel Capacity Utilization	Annual growth in U.S. steel capacity utilization. Source: U.S. Geological Survey - Iron and Steel Statistics.
Steel Import Growth	Annual growth in total imported quantities (in metric tons) into the US. Source: U.S. Geological Survey - Iron and Steel Statistics.
Steel Production Growth - U.S.	Annual growth in U.S. steel production (in metric tons). Source: U.S. Geological Survey - Iron and Steel Statistics.
Steel Production Growth - Global	Annual growth in global steel production (in metric tons). Source: U.S. Geological Survey - Iron and Steel Statistics.
US GDP growth	Quarterly growth in U.S. GDP. Source: BEA.