Real Effects of Price Transparency: Evidence from Steel Futures*

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Abstract

I study the real effects of product price transparency on producers and their customers. I use the introduction of steel futures at the London Metal Exchange and the New York Mercantile Exchange in 2008 as a quasi-natural experiment. I exploit the fact that the futures market did not become a new venue for buying physical steel and did not change firms' hedging behavior significantly. Instead, the creation of the futures market increased price transparency in the product market. I compare steel products with futures traded on the exchanges to other steel products in a difference-in-differences setting. I find that price transparency reduces prices, producer surplus and customer material costs. Price transparency further reduces input cost dispersion within narrowly defined customer industries and increases the market share of low-cost producers and aggregate producer productivity.

Keywords: Price Transparency, Real Effects of Financial Markets

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1 Introduction

Price information is central to the efficient functioning of markets. Accordingly, price transparency is an increasingly popular policy tool as evidenced by recent regulations in healthcare, finance and consumer goods industries.[1] But despite its prominent role in economic theory and its relevance for public policy, price transparency has received relatively little attention in the empirical literature, mainly due to the lack of suitable settings. In particular, how improved price transparency affects the good producing and buying firms, the allocation of ressources and productivity remains an open question.

In theory, increasing price transparency reduces prices, price dispersion, producer profits and customer costs (e.g. Janssen, Pichler, and Weidenholzer (2011)). Transparency also enables customers to identify low-cost producers, increasing matching efficiency and aggregate producer productivity (Duffie, Dworczak, and Zhu (2017)). The main empirical challenge is to isolate the effects of price transparency. In the ideal experiment, price transparency is introduced without affecting other dimensions of the market. For instance, the diffusion of the internet arguably reduced search costs and increased price transparency, but also drastically altered firms' distribution networks and product offerings.

To solve this identification problem, I use the introduction of steel futures as a quasi-natural experiment. Steel is sold from steel producers to their customers in an opaque forward market.[2] When steel futures were introduced, steel market participants were now able to observe the market price for futures of the affected products, discovered on a centralized exchange. Importantly, steel futures contracts are usually cash-settled with very little actual

[1]Christensen, Floyd and Maffett (2017) describe a number of price transparency regulations adopted in the U.S. healthcare sector in the past decade. The introduction of post-trade transparency in the U.S. corporate bond market by FINRA in 2003 is a widely studied case of price transparency regulation in financial markets. Chintagunta and Rossi (2016) study price transparency regulation in the retail gasoline market in 2007. Another example is the U.S. Department for education College Affordability and Transparency Center that compares tuition fees and net prices across universities and was launched in 2011.

[2]According to Steel Market Update, an information service provider for steel buyers, steel is sold with lead times of one to three months and predicting the future price of steel is key to succeeding in price negotiations with steel producers.

physical delivery taking place. Thus, the futures market did not simply offer a new venue to buy physical steel and did not alter firms' production and distribution networks. Further, the futures market did not change firms' hedging behavior significantly. This allows me to isolate the informational role of the newly created market. Moreover, the two steel futures contracts introduced in 2008 were for specific steel products: The London Metal Exchange (LME) introduced a contract for billets, while the New York Mercantile Exchange (NYMEX) introduced a contract for hot-rolled coils. Thus, I employ a difference-in-differences (DID) strategy to estimate the effect of the increase in price transparency brought about by the futures market on steel prices, steel producers and their customers. I compare steel products with futures traded on the exchange to other steel products and map these products to steel producing firms and their customers.

I start by examining the effect of price transparency on steel prices. Janssen, Pichler, and Weidenholzer (2011) and Duffie, Dworczak, and Zhu (2017) model price transparency as a reduction in uncertainty about production cost in a sequential search framework. When customers learn about producers' cost they can use this information in their decision whether to buy from a given producer or to continue to search. This leads to a reduction in expected prices charged by producers. In my empirical setting, when steel futures are introduced steel customers can use the information contained in the futures prices in their decision whether to buy from a given steel producer or to search for a better offer.[3] In line with the theory, I find that prices for treated steel products drop by nine percent relative to control steel products right after the introduction of steel futures. Treated and control product prices follow similar prior trends, and the effect persists five years after the introduction.

I then turn to steel producing firms. In theory, as the increase in transparency brought about by the futures market reduces expected prices, producer profit margins decrease. In the baseline specification, I map the treated products to producers using the product descriptions of six-digit NAICS industries. I find that right after the introduction of steel futures treated producer profit margins drop by five percentage points relative to control steel producers. The results are robust to refining the assignment into treatment using producers'

[3] In line with this intuition, Steel Market Update recommends to use the futures price of steel as the first reference point in negotiations with steel producers. Table A.1 shows the anecdotal evidence.

sales covariation with the treated product price indices and information from 10-K filings.

Next, I ask how increased price transparency affects steel customers. The drop in expected prices for steel products reduces their material costs. Further, the theory predicts that price transparency reduces the equilibrium price dispersion of treated steel products, decreasing the dispersion of material costs among affected steel customers. I use the Bureau of Economic Analysis (BEA) input-output table to link steel producing industries to their customer industries. I find that an increase in treated steel materials out of total materials by one standard deviation (eight percentage points) decreases material costs by 0.8 percent. Moreover, the dispersion of customer material costs measured by the coefficient of varation[4] decreases by 1.5 percentage points when the fraction of treated inputs increases by one standard deviation (five percentage points).

I then examine if the improved price transparency increases matching efficiency and aggregate producer productivity. Duffie, Dworczak, and Zhu (2017) model the effects of price transparency when producer cost are heterogenous. Producers' total cost are composed of a common and an idiosyncratic cost component. They show that if search costs are sufficiently low, revealing the common cost component leads all customers to buy from low-cost producers. In my setting, when the futures market is introduced, customers are better able to assess whether a price offer is high due to the common or the idiosyncratic component of production cost. This improves matching efficiency and increases the market share of low-cost producers. To identify low-cost producers, I exploit the fact that steel is made either from iron ore using basic oxygen furnaces (BOF) or from steel scrap using electric arc furnaces (EAF). Due to the lower cost of steel scrap, producing steel with electric arc furnaces is cheaper than with basic oxygen furnaces (Fruehan, 1998). I classify steel producers that report operating an electric arc furnace in their 2002 10-K filings as low-cost producers.[5] I find that the aggregate market share of low-cost producers increases by 20 percentage points. This aggregate increase translates into an average 1.4 percentage point

[4]The coefficient of variation is defined as the standard deviation scaled by the mean and is standard in the price dispersion literature.

[5]I measure firm and industry characterstics in 2002, before the LME as the first exchange announced in 2003 plans to launch steel futures.

increase in market-share for each low-cost producer in the treatment group relative to the control group. Further, I find that aggregate producer total factor productivity increases by eight percent. Assuming there are no within firm productivity gains, this suggests that the difference in productivity of low and high-cost producers is 50 percent. In comparison, Syverson (2004) finds that the productivty difference between the 90th and 10th percentile in the average four-digit SIC manufacturing industry is 90 percent.

One concern is that the drop in prices and producer profit margins is driven by a deterioration in demand conditions for treated steel products relative to control steel products. In particular, the Great Recession that started in 2007 and the housing bust might have affected treated and steel products differently. However, customers of treated steel products do not experience a decrease in profit margins relative to other steel customers. Further, there is no evidence of a reversal of the drop in prices and producer profit margins when the economy and the steel industry recovers. Additionally, treated steel producers do not decrease their scale of operations as measured by assets, sales or quantities sold relative to control producers. I also verify that treated and control producers exhibit a similar sensitivity to overall GDP and to construction sector employment before the introduction of steel futures. The results are also robust to controlling for exposure to overall economic activity and the construction sector directly. I also run a plabeco test around the recession of 2001 and do not find a similar pattern. Finally, I examine the stock market reactions to the announcement of the LME and NYMEX to launch steel futures contracts. If the drop in prices and producer profit margins is related to the introduction of steel futures rather than driven by demand conditions, stock prices of treated producers should drop at the day of the announcement relative to control producers. If customers pass the cost savings due to lower material prices only partially on to their customers, stock prices of treated customers should increase relative to control customers. Reassuringly, I find that treated producer stock prices decrease, whereas treated customer stock prices increase relative to the respective control group on the announcement dates of the LME and NYMEX.

Another concern is that differences in import competition, especially from China, between treated and control industries are driving the results. I show that import competition did not intensify for treated industries relative to control industries. The results are also robust to controlling for import competition as well as import competition from China.

One further concern is that the results are driven by changes in the risk managment choice set rather than price transparency. Treated steel producers might hedge more of their output price risk after the introduction of steel futures. In the presence of financing frictions, this could increase investment in productive capacity and aggregate production volumes, and decrease equilibrium prices. However, trading volumes on the exchanges, while significant in absolute terms, are low relative to steel production. Further, treated steel producers do not increase their hedging activity. They are not more likely to report derivative income or losses after the introduction of the futures market. They also do not increase investment or their scale of operations. Another risk management related concern is that steel producers implicitly sell price insurance to their customers by offering fixed-price contracts. With the creation of the futures market, steel customers can obtain input price insurance through hedging on the exchange. This may reduce the profits made by steel producers on these implicit insurance contracts. However, I find that the reduction in profit margins is not concentrated among steel producers who in the data appear to offer more stable prices to their customers.

Another potential concern is that the introduction of the futures market increases standardization of products in the treated industry. Customers may adapt their production technologies to process the exact type of steel for which futures are traded on the exchange. Higher standardization might increase competition between producers and decrease prices, producer profit margins, and customer material costs. However, using Hoberg and Phillips' (2016) text-based measure of product similarity between firms, I do not find any evidence for increased standardization in the treated industry.

This paper contributes to the literature on price transparency. There is a significant body of evidence showing that the introduction of post-trade transparency in the U.S. corporate bond market reduces bid-ask spreads (Bessembinder, Maxwell, and Venkataraman (2006), Edwards, Harris, and Piwowar (2007), Goldstein, Hotchkiss, and Sirri (2007) and Asquith, Covert, and Pathak (2013)). There is also a literature on price transparency in non-financial markets. Devine and Marion (1979) find that mandatory disclosure of supermarket prices in a local newspaper in Canada reduces prices by seven percent relative to the control group.

In contrast, Albæk, Møllgaard, and Overgaard (1997) find that following the publication of ready-mix concrete prices through the Danish antitrust authority prices increase by 15 to 20 percent. They argue that increased price transparency facilitates collusion and reduces price competition. More recently, Chintagunta and Rossi (2015) find that mandatory price signs on highways in Italy reduce gas stations' prices, but find no effect on price dispersion. Grennan and Swanson (2016) provide evidence that joining a benchmarking database leads to lower prices paid by hospitals. Christensen, Floyd, and Maffett (2017) find that regulation mandating hospitals to post their charges online, decreases charges by six percent but does not lower actual payments. This paper goes beyond prices and documents the real effects of price transparency for producers and customers in an important intermediate input market.

A related literature studies how the diffusion of the internet affects markets. There is a growing literature that studies how the internet affects prices and price dispersion (see Baye, Morgan, and Scholten (2006) for a survey). Goldmanis, Hortaçsu, Syverson, and Emre (2010) examine in an investigative study the effect of e-commerce on supply-side industry structure. They model the arrival of e-commerce as a leftward shift in the distribution of consumer search costs and, similar to Duffie, Dworczak, and Zhu (2017), predict a decline in equilibrium prices and price dispersion and an increase in low-cost producer market share. They test the model for travel agencies, bookstores, and new car dealerships. Using establishment size as a proxy for production cost, they show that an increase in the fraction of consumers buying online in an area is associated with a decrease in the number of small establishments. In contrast to their paper, I focus more narrowly on the effects of price transparency. When the fraction of consumers buying online increases, it affects the industry structure in a variety of ways other than through price transparency. Bar-Isaac, Caruana, and Cuñat (2012) argue that reductions in consumer search cost drastically change firms' product offerings and strategies. A good example of how reductions in search cost affect an industry is the case of Amazon.com which revolutionized first the book-selling industry and later retail industries for a variety of consumer goods. The internet allows consumers to learn about product offerings without visiting stores, which drastically changes optimal warehousing, distribution networks, and product offerings. One advantage of the steel industry is that the product mix is remarkably steady over time (Collard-Wexler and De Loecker (2015)).

Further, I also directly document the effect of price transparency on affected firms.

This paper also contributes to the literature on the real effects of financial markets. The extant literature focuses on how financial markets improve individual firms' investment and production decisions (see Bond, Edmans, and Goldstein (2012) for a survey). Brogaard, Ringgenberg and Sovich (2017) are closest to this paper. They argue that the increase in index investing in existing commodity futures markets reduces the informational content of commodity future prices, which leads to worse production decisions and lower profits by firms mentioning the affected commodities in their 10-K filings. In contrast, in this paper, I show that by increasing price transparency the introduction of the futures market for steel reduces informational asymmetries between producers and customers.

In terms of methodology, two papers use the introduction of new derivatives markets as an experiment. Pérez-Gonzaléz and Yun (2013) argue that the introduction of weather derivatives improves weather-sensitive firms' ability to hedge, leading to increased valuation, investment, and leverage. Almeida, Hankins, and Williams (2017) also use the introduction of steel futures to show that firms use purchase obligations as a risk management tool. Both papers focus on the risk management implications of derivative markets, whereas this paper focuses on the informational implications.

This paper also relates to the literature on misallocation. Hsieh and Klenow (2009) estimate that reallocation of inputs across firms could increase total factor productivity by 30 to 60 percent. Onishi (2016) argues that quantity discounts in the aircraft industry lead to price dispersion and misallocation of aircrafts in the airline industry. This paper shows that a lack of price transparency can be one barrier to efficient ressource allocation across firms. First, opaqueness hinders high-productivity producers to capture more market share. Second, opaqueness increases the input cost dispersion of intermediate good buyers. Such firm-level distortions of factor prices may lead to inefficient allocation. In this paper, I show that price transparency increases low-cost producer market share and aggregate producer total factor productivity and reduces input cost dispersion in customer industries.

The paper proceeds as follows. Section 2 describes the institutional environment. Section 3 briefly presents the theoretical framework and derives the predictions tested in this paper. Section 4 discusses the identification strategy. Section 5 describes the data. Section 6 presents the results. Section 7 discusses alternative explanations. Section 8 concludes.

2 Institutional Environment

2.1 Industry Background

According to the American Iron and Steel Institute (AISI), raw steel is produced in two principle ways. Basic oxygen furnaces (BOF) use pig iron, made from iron ore, coal and limestone in a blast furnace, and 25 to 35 percent steel scrap to produce new steel. Electric arc furnaces (EAF) use 100 percent steel scrap.[6] In 2001, about 53 percent of steel in the U.S. was produced in blast furnaces, and the remaining 47 percent in electric arc furnaces (Rogers (2002)).

Both processes produce molten steel which can be solidified into semi-finished steel products of different shapes and for different uses and further processed through casting, forging or rolling. Semi-finished products are categorized into slabs, blooms and billets based on their height and width. These semi-finished products can be reheated and further processed. Slabs are either processed into plates and pipe products or into hot-rolled sheets or coils. Hot-rolled coils may then further be processed into pickled and oiled coils, cold-rolled coils and sheets and coated coils. Blooms and billets are processed into seamless tubes, structural mill products or bars and rods. Table 1 shows U.S. steel production for the major product groups. The steel industry is a competitive industry. In 2002 there were 67 public firms operating in steel producing industries.

2.2 Introduction of Steel Futures

In April 2008 trading in steel billet futures started at the London Metal exchange (LME) and in October 2008 hot-rolled coil futures startet trading at the Ney York Mercantile Exchange (NYMEX). This raises the question of why steel futures were introduced in 2008 and why these particular products were chosen by the exchanges.

[6] Direct reduced iron (DRI) can be used as a substitute for steel scrap in electric arc furnacess, but is typically more expensive than steel scrap.

Carlton (1984) argues that one necessary condition for the success of futures contracts is price volatility. As shown by Figure 1 steel price volatility increased largely before the LME as the first exchange announced to start working on launching steel futures contracts in 2003. Reassuringly, the rise in steel price volatility is observed for both eventually treated and control steel products. This increase in steel price volatility created the necessary demand for derivatives to manage steel price risk.

In the decision which steel products to use as an underlying in the futures contract, exchanges face a trade-off between minimizing basis risk and maximizing liquidity. Offering a futures contract for each steel product would mimimize the basis risk for each product but would lower liquidity in each contract as total trading volume is split across the products. The emergence of steel futures contracts for billets at the LME and hot-rolled coils at the NYMEX reflects this trade-off. Steel future contracts have been introduced for other products in other parts of the world.[7] This shows that the decision by the LME and NYMEX were not driven by unique product features of billets and hot-rolled coils. However, steel is sold in largely regionally segmented markets. The NYMEX contract is based on U.S. mid-west hot-rolled coils. The LME contract has multiple points of delivery in the U.S. As the focus of this paper are Northamerican firms I only consider the NYMEX and LME contracts following Almeida, Hankins, and Williams (2017).

Next, I turn to the question of how steel futures affected steel producers and their customers. First, to isolate the effect of price transparency it is important that the futures market did not simply become an alternative way to buy physical steel. The NYMEX contract is cash-settled without the possibility of physical delivery. The billet futures contract has the option of physical delivery. But according to the LME physcial delivery is very low as traders usually close their position before actual delivery. Second, as shown in Table A.2, although trading volume is significant in absolute terms, it is low relative to overall steel production. This makes it unlikely that changes in the risk management practices of

[7] In the sample period futures traded for reinforcing bars in Dubai and Shanghai, for ingots and hot-rolled coils in India, and wire rod in Shanghai. Trading volumes in Dubai and India are small and trading in Shanghai is restricted to Chinese traders. Steel imports from China, India and the United Arab Emirates combined average 2.7 percent in the sample period.

firms had a large effect on steel producing industries and their customers. Further, I do not find evidence that treated producers increased their hedging activity relative to control producers. I adress hedging related alternative explanations in section 6.

Instead I argue that steel futures increased price transparency for steel products traded on the exchange. Unlike other metal markets, prices for steel are not controlled by a public auction, which makes information about producers' production cost and overall market conditions crucial for customers. There are price indices published by the Bureau of Labor Statistics (BLS) and private data collectors. However, these indices are based on voluntary surveys and published with a delay, whereas according to Steel Market Update steel is usually sold forward with lead times of one to three months. Thus, steel futures provide valuable information to customers about the future price of steel. In line with this intuition, Steel Market Update recommends to use the futures price of steel as the first reference point in negotiations with steel producers. Further, steel producer executives strongly opposed the introduction of the futures market for steel, fearing to loose control over pricing. Table A.1 presents the anecdotal evidence.

3 Theoretical Framework

To derive the predictions tested in this paper I borrow from Janssen, Pichler, and Weidenholzer (2011) and Duffie, Dworczak, and Zhu (2017). The effect of price transparency is modeled by comparing the case where customers know producers' production cost to the case where customers do not know the production cost in a sequential search market.

In the setting of Janssen, Pichler, and Weidenholzer (2011), producers maximize profits taking prices charged by competitors and customer search behavior as given. Upon observing a price offer, customers can either buy or pay a search cost to obtain one additional offer. A fraction λ of customers, the *shoppers*, have zero seach cost, obtain price offers of all producers and buy at the lowest price. The remaining fraction of *nonshoppers* pays search cost greater than zero and trades off the search cost against the expected benefit from search. Customers buy if the observed price p is below their reservation price r, continue to search if $p > r$ and are indifferent if $p = r$. A standard result in the search literature is that for

$\lambda \in (0, 1)$ producers follow a mixed-strategy and draw price offers from the cumulative price distribution F as they trade off setting low prices to attract shoppers with setting high prices to extract rents from selling to nonshoppers.[8] The upper bound of the price distribution F is given by the reservation price, as no producer sets a higher price than the reservation price in equilibrium.

In the transparent market, customers can condition on the production cost and their reservation price is then given by the production cost c plus a mark-up proportional to the search cost. In the opaque market, customers do not observe the production cost and shoppers can only condition on price offers they observe in their decision to buy or continue to search. The upper bound of the price distribution is then given by the first round reservation price. Janssen, Pichler, and Weidenholzer (2011) show that this first round reservation price is higher than the reservation price in the transparent equilibrium. Thus, expected prices, producer profits and the expected price spread between the highest and the lowest prices in the market are higher and customer surplus is lower compared to the case where production cost are known. Intuitively, in the opaque market producers strategically exploit that customers are uninformed about their production cost, and set on average higher prices compared to the transparent case.

In my empirical setting, the introduction of steel futures increased price transparency for the steel products with futures traded on the exchange, moving the market for these products from the opaque to the transparent equilibrium. This increase in transparency leads to the following predictions:

> ***Prediction 1:*** *Expected prices charged by producers decrease in response to increased price transparency.*

> ***Prediction 2:*** *Producer profit margins decrease in response to increased price transparency.*

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[8] If $\lambda = 1$ the equilibrium in pure strategies is the Bertrand equilibrium where all producers charge prices equal to their marginal cost. If $\lambda = 0$ the equilibrium in pure strategies is the Diamond (1971) paradox, where all firms charge the monopoly price.

Prediction 3: *Customer material costs decrease in response to increased price transparency.*

Further, as the spread between the lowest and highest prices charged by producers is lower in the transparent compared to the opaque market, the increased price transparency brought about by the futures market decreases dispersion in customers' material cost.

Prediction 4: *Dispersion in customer material cost decreases in response to increased price transparency.*

Duffie, Dworczak, and Zhu (2017) extend the analysis to include heterogeneity in producer cost. Producers' total cost are composed of a common and an idiosyncratic cost component and price transparency reveals the common cost component c. They show that if search costs are sufficiently low, price transparency leads all customers to buy from low-cost producers. Knowing the common cost component c allows customers to distinguish between efficient and inefficient producers. In the opaque market, where customers do not know the common cost component, they can only rely on observed prices. However, when the realization of the common cost component c is low, high-cost producers can offer prices that low-cost producers would make under higher realizations of c. Nonshoppers then buy from high-cost producers. Revealing the common cost component allows customers to distinguish between high prices from low-cost producers under high cost realizations and low prices from high-cost producers under low cost realizations. In my empirical setting, the increased price transparency brought about by the introduction of the futures market increases customers ability to assess whether a high price offer is due to the common or the idiosyncratic component of production cost. This improves matching efficiency and increases the market share of low-cost producers.

Prediction 5: *Low-cost producer market share increases in response to increased price transparency.*

Finally, as low-cost producers increase their market share, aggregate total factor productivity increases in the producer industry.

Prediction 6: *Aggregate producer total factor productivty increases in response to increased price transparency.*

4 Identification Strategy

4.1 Difference-in-differences estimation

To assess the effect of price transparency, I use a difference-in-differences (DID) estimation and compare steel products with futures traded on the exchange to other steel products before and after the introduction of steel futures. This strategy allows to control for shocks that affect the steel industry as a whole. Futures were introduced for billets in April 2008 at the LME and for hot-rolled coils in October 2008 at the NYMEX. In this section I describe the specification to estimate the effect of price transparency on product prices. I present adapted specifications to test the predictions on producers and customers right before discussing the result.

To estimate the effect of price transparency on the level of prices, I estimate the following OLS regression at the product-month level in the sample of steel industries,

$$\textit{Log(Price-Index)}_{p,t} = \beta \times \textit{Post-Treated-Product}_{p,t} + \delta_p + \eta_t + \varepsilon_{p,t} \tag{1}$$

where p indexes products and t indexes year-months. $\textit{Log(Price-Index)}_{p,t}$ is the log of the price index in year-month t for product p, δ_p are product fixed effects, η_t are year-month fixed effects, and $\varepsilon_{p,t}$ is the error term. The main variable of interest, $\textit{Post-Treated-Product}_{p,t}$, is a dummy variable equal to one for billets after April 2008 and for hot-rolled coils after October 2008. I cluster standard errors at the industry and year-month level. The coefficient of interest β measures the change in prices after the introduction of steel futures for treated relative to control steel products.

4.2 Internal Validity

The key identifying assumption in this setting is that, if the steel futures market had not been introduced, treated steel products would have moved in the same way as control steel products moved.

This identifying assumption cannot be tested directly, but I verify that treated and control steel products follow parallel trends in the period before the introduction. Figure 2 presents the evolution of steel prices from the beginning of the sample period in 2003 (five years before the introduction) until the end of the sample period in 2013 (five years after the introduction) for eventually treated and never treated steel products. The graph shows that eventually treated and never treated products follow similar trends prior to the introductions of steel futures in April and October 2008. Figure 3 presents the evolution of steel producer profit margins for eventually treated and never treated steel producers during the sample period. Again, the graph shows that eventually treated and never treated producers follow similar trends prior to the introduction of steel futures. In section 6, I also analyze the dynamics of the effect and show that the effect of steel futures only starts after the introduction.

5 Data

5.1 Prices

I use price indices from the Bureau for Labor Statistics (BLS) Producer Price Index (PPI) series. These indices are based on voluntary surveys of systematically selected samples of establishments that produce the product and published around two weeks after the reference month.[9] I restrict the sample to steel products with full price index information during the sample period.

5.2 Firm Characteristics

To measure firm characteristics I use accounting data from Compustat Northamerica. I use historical NAICS codes for the year 2002 to assign firms into treatment and control industries. I measure profit margins as operating income over sales and material costs as cost of goods sold over sales. I also compute the log of assets, leverage ratio and sales-to-assets ratio in 2002. To measure the stock market reaction to the exchanges' announcements, I use daily

[9] Once an establishment agrees to cooperate it reports prices for selected products until a new sample is selected for the industry after 7 to 8 years. Currently around 25,000 establishments report their monthly prices. In comparison, there were 7,663,938 establishments in the U.S. according to the latest Statistics on U.S. Businesses (SUSB) in 2015.

stock prices from CRSP. All variables are winsorized at the 1st and 99th percentile.[10]

5.3 Customers

To identify steel customer, I use the 2002 Bureau of Economic Analysis (BEA) input-output table. For each four-digit downstream industry j, I compute the fraction of inputs from steel producing industries,

$$\textit{Steel-Input}_j = \frac{\sum_k \textit{Steel-Producer}_k \times \textit{Gross-Flow}_{j,k}}{\sum_k \textit{Gross-Flow}_{j,k}},$$

where $\textit{Steel-Producer}_k$ is a dummy variable equal to one if upstream industry k produces steel, and $\textit{Gross-Flow}_{j,k}$ is the gross-flow from upstream industry k to downstream industry j. I then compute the fraction of inputs for which futures become available in 2008,

$$\textit{Future-Steel-Input}_j = \frac{\sum_k \textit{Future-Steel-Producer}_k \times \textit{Gross-Flow}_{j,k}}{\sum_k \textit{Gross-Flow}_{j,k}},$$

where $\textit{Future-Steel-Producer}_k$ is a dummy variable equal to one if upstream industry k produces steel traded on either the LME or NYMEX. I compute *Steel-Material* and *Future-Steel-Material* using analogous calculations, excluding upstream industries that do not produce physical goods.[11] Further, I compute *Future-Steel* as the fraction of inputs from treated producer industries over total steel inputs.

To measure customer input cost dispersion, I compute the coefficient of variation for $COGS/Sales$, defined as the standard deviation (SD) scaled by the mean, for each year-quarter within each four-digit industry,

$$CV(COGS/Sales)_{j,t} = \frac{SD(COGS/Sales)_{j,t}}{\overline{(COGS/Sales)}_{j,t}}.$$

5.4 Low-Cost Producer Market Share and Producer Productivity

To measure the market share of low-cost producers I first use steel producers' 10-K filings to identify low-cost producers. The dummy variable $\textit{Low-Cost Producer}_i$ equals one if a steel

[10] All results are robust to using non-winsorized variables.

[11] Materials are defined as inputs from physical goods producing industries, excluding NAICS codes 1150, 2130, 2211, 23, and 4 to 8.

producer's 2002 10-K filing mentions operating an electric arc furnace. I then compute for the treatment and control group the market share of low-cost producers for each year-quarter,

$$\textit{Low-Cost Producer Market Share}_{g,t} = \frac{\sum_i \textit{Low-Cost Producer}_i \times \textit{Sales}_{i,g,t}}{\sum_i \textit{Sales}_{i,g,t}}.$$

Finally, to measure aggregate producer productivity I use the NBER-CES manufacturing database. The NBER-CES data provides yearly total factor productivity measures at the six-digit NAICS code level and is available until 2011.

6 Results

6.1 Summary Statistics

Table 2 presents summary statistics. Panel A compares treated and control producers in 2002. Treated steel producers are larger and have sligthly lower leverage and sales-to-assets ratios than control producers. To ensure that the results are not driven by differences between firms, I include a vector of firm-level characteristics interacted with the *Post* dummy in the producer regressions. In Panel B I split the sample of steel customer industries in 2002 at the median of $\textit{Future-Steel}_j$, the fraction of treated steel inputs out of total steel inputs. Steel customers above the median use less capital and have higher sales-to-capital ratios. To ensure that the results are not driven by differences between customer industries, I include a vector of industry-level characteristics interacted with the *Post* dummy in the customer regressions.

6.2 Prices

I begin by testing whether increased price transparency leads to lower prices (Prediction 1). To estimate the effect of price transparency on the level of prices, I use the BLS Producer Price Indices for steel producing industries and I estimate equation 1 at the product-month level in the sample of steel industries.

Table 3 presents the DID estimate for the effect of the introduction of steel futures on the level of prices. Prices of treated products drop by seven to ten percent relative to control products. The effect is robust to controlling for product-specific time-trends in column (2), initial product characteristics in column (3), and business cycle and import competition controls in columns (4) and (5). Columns (1) and (2) restrict the sample to include only products within the same six-digit industry as the treated products. Columns (3) to (5) include all steel products presented in Table 1. Next, I estimate the dynamics of the effect. The results in Panel A of Figure 4 show that there is a sharp drop in prices right after the introductions of the steel futures contracts.

6.3 Producer Profit Margins

I then test whether price transparency reduces producers' profit margins (Prediction 2). To estimate the effect of price transparency on producer profit margins, I map the treated products to steel producers. I start with all Compustat firms operating in steel producing industries during the sample period. Industries are defined at the six-digit NAICS code level. In the baseline specification I use NAICS product descriptions to map the treated products to six-digit industries. As shown in Table 1, billets and hot-rolled coils are produced in NAICS 331111. I then assign firms into the treatment and control group based on their industry in 2002, before the LME first announced their plans to launch steel future contracts in 2003.[12] I estimate the following OLS regression at the firm-quarter level in the sample of steel producing industries,

$$\frac{Profit_{i,j,t}}{Sales_{i,j,t}} = \beta \times Post \times Treated_j + \delta_i + \eta_t + \varepsilon_{i,j,t} \tag{2}$$

where i indexes firms, j indexes industries at the six-digit NAICS level, and t indexes year-quarters. δ_i are firm fixed effects, η_t are year-quarter fixed effects, and $\varepsilon_{i,j,t}$ is the error term. The dummy variable $Treated_j$ is equal to one for treated producers. The dummy variable *Post* is equal to one after Q2 2008. To account for potential differences between treated and control firms, I introduce controls for initial firm characteristics. I interact the log of assets, leverage and sales-to-assets ratio measured in 2002 with the *Post* dummy. To account for different time trends for treated and control producers, I also introduce separate

[12]No treated firms change industries during the sample period.

time trends for each industry. I cluster standard errors at the industry and year level. The coefficient of interest β measures the change in profit margin after the introduction of steel futures for treated relative to control steel producers. Table 4 presents the DID estimates for the effect of the introduction of steel futures on producer profit margins. I find that treated producer profit margins drop by five to nine percentage points relative to control producers. The effect is robust to controlling for initial firm characteristics in column (2) and industry-specific time-trends in column (4). In columns (1) and (2) I use all firms in steel producing industries in Compustat. I restrict the sample to firms with headquarters in the North American Free Trade Agreement (NAFTA) region in columns (3) to (6). The results are robust to refining the assignment into treatment using the covariation of firm sales with the treated products and information from firms' 10-K filings, reported in Table A.10 and A.11 in the Appendix. The dynamics of the effect are shown in Panel B of Figure 4. Treated producer profit margins drop sharply after steel futures are first introduced.

One concern in this setting is that the drop in prices for treated steel products and producer profit margins is driven by other events in that time period which impacted treated and control steel products differentially. Steel futures might have been introduced at a time when demand conditions for treated steel products deteriorated relative to control products. In particular, the Great Recession might have had a stronger negative impact on treated steel products. A related concern is that treated and control products might differ in their exposure to the construction sector. The bust in the housing sector might have affected treated products more than control products.

I conduct several tests to adress these crisis-related concerns. First, as shown in Table A.3, customers of treated steel products do not experience a decrease in profit margins relative to other steel customers. The point estimates are not statistically significant at conventional levels and positive, showing no evidence for a stronger weakening in demand conditions for customers of treated steel products. Second, I find no evidence of a reversal in producer profit margins when the steel industry recovers in 2012, as shown in Table A.4. The point estimate on the interaction of the *Treated* dummy with a dummy variable equal to one after 2012 is not significant and negative. Third, as shown in Table A.5, treated steel producers do not decrease their scale of operations relative to control steel producers, measured by the log of assets, sales and quantities sold.[13] All three point estimates are not significant and positive. Fourth, as shown in Table A.6, treated and control producers exhibit a similar sensitivity to real GDP and to the construction sector before the introduction of steel futures. I regress a firm's beta with respect to real GDP and constuction sector employment, estimated during the ten years prior to the introduction (1998 to 2007), on the *Treated* dummy. The point estimates are not significant and negative. Next, I run a placebo test and re-run the producer profit margin regressions around the recession of 2001 to test if treated steel producers' profit margins drop in general more in recessions.[14] Table A.7 shows no differential development of profit margins for treated and control producers around the recession in 2001. The point estimates are not significant and positive.

Another concern is that differences in import competition, and in particular import competition from China, between treated and control firms are driving the results. Table A.8 shows that import competition did not intensify for treated relative to control industries after the introduction of steel futures. The point estimates are not significant and negative.

Next, I examine the stock market reactions to the announcement of the LME and NYMEX to launch steel futures contracts. If the drop in prices and producer profit margins is related to the introduction of steel futures rather than driven by demand conditions or import competition, I expect stock prices of treated producers to drop at the day of the announcement relative to control producers. If customers pass the cost savings due to lower material prices only partially on to their customers, stock prices of treated customers should increase relative to control customers. I construct portfolios for treated and control producers and customers for the announcements by the LME and NYMEX respectively. I then run the following OLS regression,

$$Return(Treated - Control)_t = \beta \times AnnouncementDay_t + \gamma' F_t + \varepsilon_t, \quad (3)$$

where t indexes day, $Return(Treated - Control)_t$ is the return on a portfolio that is long the treated firms and short the control firms for the respective announcement. $AnnouncementDay_t$

[13] Quantities sold are measured by deflating firms' sales with industry price-indices.

[14] The corresponding NBER recession dates are: March 2001 - November 2001 and December 2007 - June 2009. www.nber.org/cycles.

is a dummy equal to one on the day of the announcement and F_t is a vector of the three Fama-French factors size, book-to-market and the market risk premium.[15] Table A.9 confirms that treated producer stock prices decrease, whereas treated customer stock prices increase relative to the respective control group on the announcement dates of the LME and NYMEX.

Finally, I also include controls for exposure to overall economic activity and the construction sector as well as for import competition. I control for the sensitivity to real GDP and to employment in the construction sector of products, firms, and industries depending on the specification, interacted with the *Post* dummy. I also control for quarterly real GDP growth and employment growth in the construction sector, interacted with the respective treatment variable. I also control for import competition as well as import competition from China in the steel industry, interacted with the treatment variable. Columns (3) to (5) of Table 3 show that the price results, and columns (2) to (6) of Table 4 show that the profit margin results are robust to including these controls.

The finding that price transparency reduces producer profit margins also allows me to contribute to an ongoing debate about the relationship between profitability and capital structure.[16] Standard trade-off theory predicts, that decreases in expected future profitability should lead to a decrease in leverage ratios, due to lower expected tax benefits of debt and higher expected costs of financial distress. In contrast, the pecking-order theory predicts a negative relationship between profitability and leverage, as firms prefer using internal funds over using debt. Numerous cross-sectional studies document a negative relationship between profitability and leverage (e.g. Baker and Wurgler (2002), Rajan and Zingales (1995), Titman and Wessels (1988)). Xu (2012) uses import competition as a shock to expected future profitability and shows that leverage decreases in response to increased import competition. In contrast, I find that leverage ratios increase by 10 percentage points

[15]The Fama-French factors were obtained from Kenneth French's website at `http://www.http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/`.

[16]I verify that profitability, measured as operating income over total assets, decreases for treated steel producers, which is epxected as profit margins decrease while sales and total assets are unaffected as shown in table A.5

for treated producers relative to control producers as shown in Table A.12 and Figure 7, in line with the pecking-order theory.

6.4 Customer Costs

Next, I test whether increased price transparency reduces customers' material costs (Prediction 3). To estimate the effect of price transparency on customer costs, I use the 2002 Bureau of Economic Analysis (BEA) input-output table to identify steel customer. I merge the information from the input-output table to the NBER-CES manufacturing database based on four-digit NAICS codes. I restrict the sample to industries with at least ten percent steel materials and exclude steel producing industries. I then estimate the following OLS regression at the industry-quarter level in the sample of steel buying industries,

$$\textit{Log(Material Prices)}_{j,t} = \beta \times \textit{Post} \times \textit{Future-Steel-Material}_j + \gamma' \textit{Post} \times X_j + \delta_j + \eta_t + \varepsilon_{j,t}, \quad (4)$$

where j indexes industries at the four-digit level, and t indexes years. δ_j are firm fixed effects, η_t are year fixed effects, and $\varepsilon_{j,t}$ is the error term. The outcome variable $\textit{Log(Material Prices)}_{j,t}$ is the log of the material price deflator. $\textit{Future-Steel-Material}_j$ is the fraction of an industry's treated steel materials out of total materials used. The vector X_j includes the fraction of an industry's steel materials out of total materials, $\textit{Steel-Material}_j$, in all regressions. I also include controls for initial industry log of capital and sales-to-capital ratio interacted with the *Post* dummy. I cluster standard errors at the industry and year level.

Table 5 shows that material costs decrease by 0.8 percent more after the introduction of steel futures when the fraction of treated steel materials, $\textit{Future-Steel-Material}_j$, increases by one standard deviation or 8 percentage points. These magnitudes are consistent with the effects on producer prices reported in Table 3. The effect is robust to controlling for initial industry characteristics, crisis-related and import competition controls in columns (2) and (3). To assess the dynamics of the effect, I interact a dummy variable equal to one if the fraction of treated steel materials out of total steel materials, $\textit{Future-Steel}_j$, is above the median with the full set of year fixed effects. Figure 5 shows that material cost start to decrease only after the introduction of steel futures.

6.5 Customer Cost Dispersion

I then test whether increased price transparency reduces customers' input cost dispersion (Prediction 4). I merge the information from the input-output table with Compustat based on 2002 four-digit NAICS codes. I restrict the sample to industries with at least ten percent steel inputs and exclude steel producing industries. I compute the coefficient of variation of *COGS/Sales* for each year-quarter within each four-digit customer industry. I then estimate the following OLS regression at the industry-quarter level in the sample of steel buying industries,

$$CV(COGS/Sales)_{j,t} = \beta \times Post \times \textit{Future-Steel-Input}_j + \gamma' Post \times X_j + \delta_j + \eta_t + \varepsilon_{j,t}, \quad (5)$$

where j indexes industries at the four-digit level, and t indexes year-quarters. δ_j are industry fixed effects, η_t are year-quarter fixed effects, and $\varepsilon_{j,t}$ is the error term. $\textit{Future-Steel-Input}_j$ is the fraction of an industry's treated steel inputs out of total inputs used.[17] The vector X_j includes the fraction of an industry's steel inputs out of total inputs, $\textit{Steel-Input}_j$, in all regressions. I also include controls for initial average industry log of assets, sales-to-asset ratio, leverage, real GDP beta and construction sector beta, interacted with the *Post* dummy. I cluster standard errors at the industry and year level.

Table 6 shows that the coefficient of variation of *COGS/Sales* decreases by 1.5 percentage points more after the introduction of steel futures when $\textit{Future-Steel-Input}_j$ increases by one standard deviation (five percentage points). The effects are robust to controlling for industry trends in column (2) and initial industry characteristics, crisis-related and import competition controls in column (3). Figure 5 shows that input cost dispersion starts to decrease only after the introduction of steel futures. Thus, transparency reduces price dispersion and decreaes prices paid by customers with high search cost relative to customers with low search cost. One implication of this result is that price transparency improves input allocation in the customer industry. Hsieh and Klenow (2009) argue that as firms equate marginal revenue to marginal cost, distortions which affect the relative prices firms' pay

[17] I use all inputs in this regression to match the outcome variable. Cost of goods sold include all costs that are directly related to the goods sold, not only materials. The results are robust to only using materials instead.

for their inputs lead to misallocation and lower aggregate output. In my setting, customers which pay higher prices have higher marginal revenue products and reducing price dispersion improves allocation.

6.6 Low-Cost Producer Market Share

Next, I test whether increased price transparency improves matching efficiency and increases the market share of low-cost producers (Prediction 5). I use information from steel producers' 10-K filings to identify low-cost producers. I classify steel producers as low-cost, if they mention operating electric arc furnaces in their 2002 10-K filing. Due to the lower cost of steel scrap, producing steel using electric arc furnaces is cheaper than using basic oxygen furnaces (Fruehan, 1998). I then compute the market share of low-cost producers in each year-quarter for the treatment and the control group and estimate the following OLS regression at the group-quarter level in the sample of steel producing industries,

$$\textit{Low-Cost Producer Market Share}_{g,t} = \beta \times \textit{Post} \times \textit{Treated}_g + \delta_g + \eta_t + \varepsilon_{g,t}, \tag{6}$$

where g indexes the treatment and control group, and t indexes year-quarters. δ_g are group fixed effects, η_t are year-quarter fixed effects, and $\varepsilon_{g,t}$ is the error term. I also introduce separate time trends for the treatment and control group. I cluster standard errors at the year-quarter level.

Table 7 shows that low-cost producer market share increases by 20 to 26 percentage points for the treated group relative to the control group after the introduction of steel futures. The effects are robust to controlling for separate time-trends for the treated and control groups in column (2), and crisis-related and import competition controls in columns (3) and (4). Panel A of Figure 6 shows low-cost producer market share starts to increase right at the introduction of steel futures. In terms of magnitudes, the aggregate increase translates to an increase of 1.4 to 1.9 percentage points for each low-cost producer in the treatment group relative to low-cost producers in the control group.[18] In Table A.13 I further show that firms' market share in the steel industry become more sensitive to proxies for productivity.

[18] There are 14 low-cost producers in the treatment group.

6.7 Aggregate Producer Total Factor Productivity

I then study whether price transparency increases aggreagte producer total factor productivity (Prediction 6). Six-digit industry total factor productivity (TFP) data are obtained from the NBER-CES manufacturing database. I estimate the following OLS regression at the industry-year level in the sample of steel producing industries,

$$Log(TFP)_{j,t} = \beta \times Post \times Treated_j + \delta_j + \eta_t + \varepsilon_{j,t}, \quad (7)$$

where j indexes industries, and t indexes years. δ_j are industry fixed effects, η_t are year fixed effects, and $\varepsilon_{j,t}$ is the error term. I cluster standard errors at the industry and year level.

Table 8 shows aggregate TFP increases by 8 percent in the treated industry relative to the control industries after the introduction of steel futures. The effects are robust to controlling for crisis-related and import competition controls in column (2). Panel B of Figure 6 shows aggregate producer TFP increases right at the introduction of steel futures. Assuming there are no within firm productivity gains, this suggests that the difference in productivity of low and high-cost producers is 50 percent.[19] In comparison, Syverson (2004) finds that the productivty difference between the 90th and 10th percentile in the average four-digit SIC manufacturing industry is 90 percent.

7 Alternative Explanations

7.1 Hedging Increases Investment and Production Volumes

One potential concern regarding the intepretation of the findings on prices, producer profit margins and the level of customer material costs is that steel futures might allow treated producers to hedge more of their output price risk. In the presence of financing frictions, this could increase investment in productive capacity, aggregate production volumes and reduce equilibrium prices, producer profit margins and customer material costs. However,

[19] In 2001, 47 percent of steel production in the U.S. used electric are furnaces. Increasing this fraction to 67 percent would lead to an increase in TFP of 8 percent if the productivity difference between low and high-cost producers was 50 percent.

as shown in Table A.2 hedging volumes are significant in absolute terms but are low relative to total steel production, never exceeding three percent of overall production. In addition, Table A.14 shows that treated producers do not increase their hedging activity, measured by a dummy variable equal to one if a producer reports income or losses from derivatives. Further, they do not increase investment or their scale of operations as measured by the log of assets, log of sales, or log of quantities sold as shown in Table A.5. Taken together, these findings are inconsistent with the view that increased hedging activity by producers is driving the results.

7.2 Hedging Reduces Producers' Implicit Insurance Profits

Another potential concern is that the existence of the futures market gives steel customers the option to obtain insurance against input price fluctuations through trading the futures contracts on the exchange. This outside option may reduce profits steel producers are generating by offering implicit price insurance to their customers through fixed-price contracts. However, according to industry participants the fraction of profits stemming from implicit price insurance to customers is negligible. Further, I do not find that steel producers who in the data appear to offer more implicit price insurance to their customers experience a larger decrease in profit margins. Producers who sell implicit price insurance offer fixed-price contracts and absorb variations in input cost without passing them on to their customers. These producers should exhibit a lower sales beta with respect to input cost. I measure producers' sales beta with respect to a cost-index of iron ore and steel scrap prices and interact this cost beta with the treatment variable. Table A.15 shows that steel producers with a lower cost beta experience a smaller decrease in profit margins, the opposite of what the insurance view predicts.

7.3 Standardization of Products Intensifies Competition

Another concern is that the introduction of the futures market increases standardization of products in the treated industry. Customers may adapt their production technologies to process the exact type of steel traded on the exchange. Higher standardization might increase competition between producers and decrease prices, producer profit margins and customer material costs. To test this view, I use Hoberg and Phillips' (2016) text-based measure of product similarity between firms.[20] Table A.16 shows that the average similarity score between a producer and its closest rival firms does not increase for treated producers relative to control producers, which is inconsistent with the view that an increase in standardization explains the results.[21]

8 Conclusion

This paper asks how price transparency affects producers, customers and aggregate productivity. To isolate the role of price transparency, I use the introduction of steel futures in 2008. The futures market increased price transparency for affected products and leads to a drop in prices by nine percent. This causes steel producer profit margins to decrease by five to nine percentage points and customer material costs to decrease. Further, dispersion in customer material costs decreases. Finally, the market share of low-cost producers increases by 20 percentage points and aggregate steel producer productivity increases by eight percent. Taken togehter, the results show that price transparency has important real effects.

[20]See Hoberg and Phillips (2010, 2016) for descriptions of the data.

[21]The table shows the result for the 10 and 20 closest firms. The results are robust to using the closest 5 or 15 firms instead.

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Figure 1: Evolution of Price Volatility Over Time

Figure 1 plots the yearly average absolute change in the monthly price indices for eventually treated and never treated steel mill products over time. Price volatility increased for both eventually treated and control products before the LME as the first exchange announced to start working on launching steel futures contracts in 2003, creating the necessary demand for derivatives to manage steel price risk.

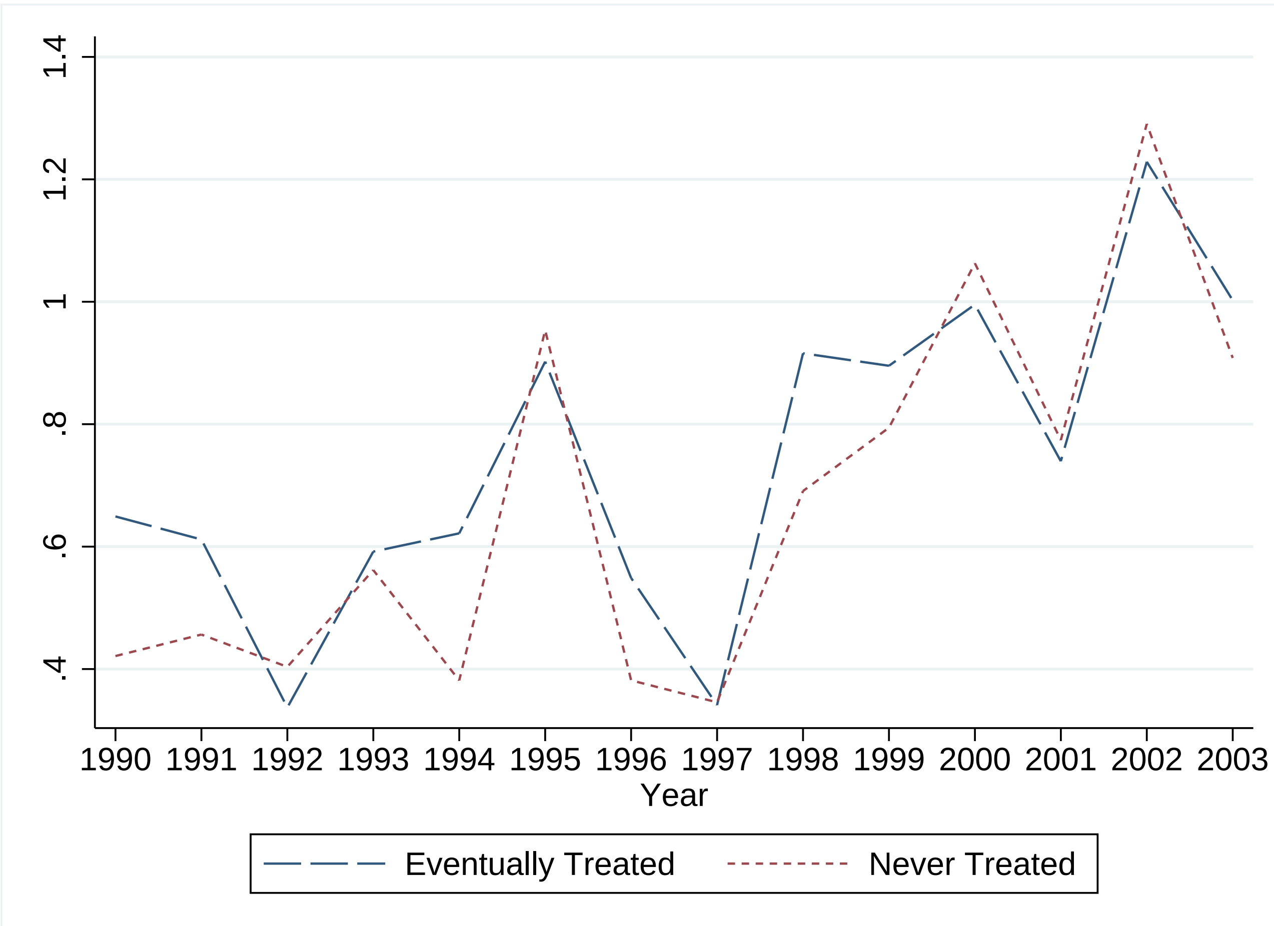


Figure 2: Evolution of Product Prices Over Time

Figure 2 plots the price indices of eventually treated and never treated steel mill products over time. The vertical grey bar indicates the introduction of the steel futures contracts. Price indices are expressed relative to their value in March 2008, before the first introduction of steel futures at the London Metal Exchange.

Figure 3: Evolution of Producer Profit Margins Over Time

Figure 3 plots the profit margin of eventually treated and never treated steel producers over time. The vertical grey bar indicates the introduction of the steel futures contracts.

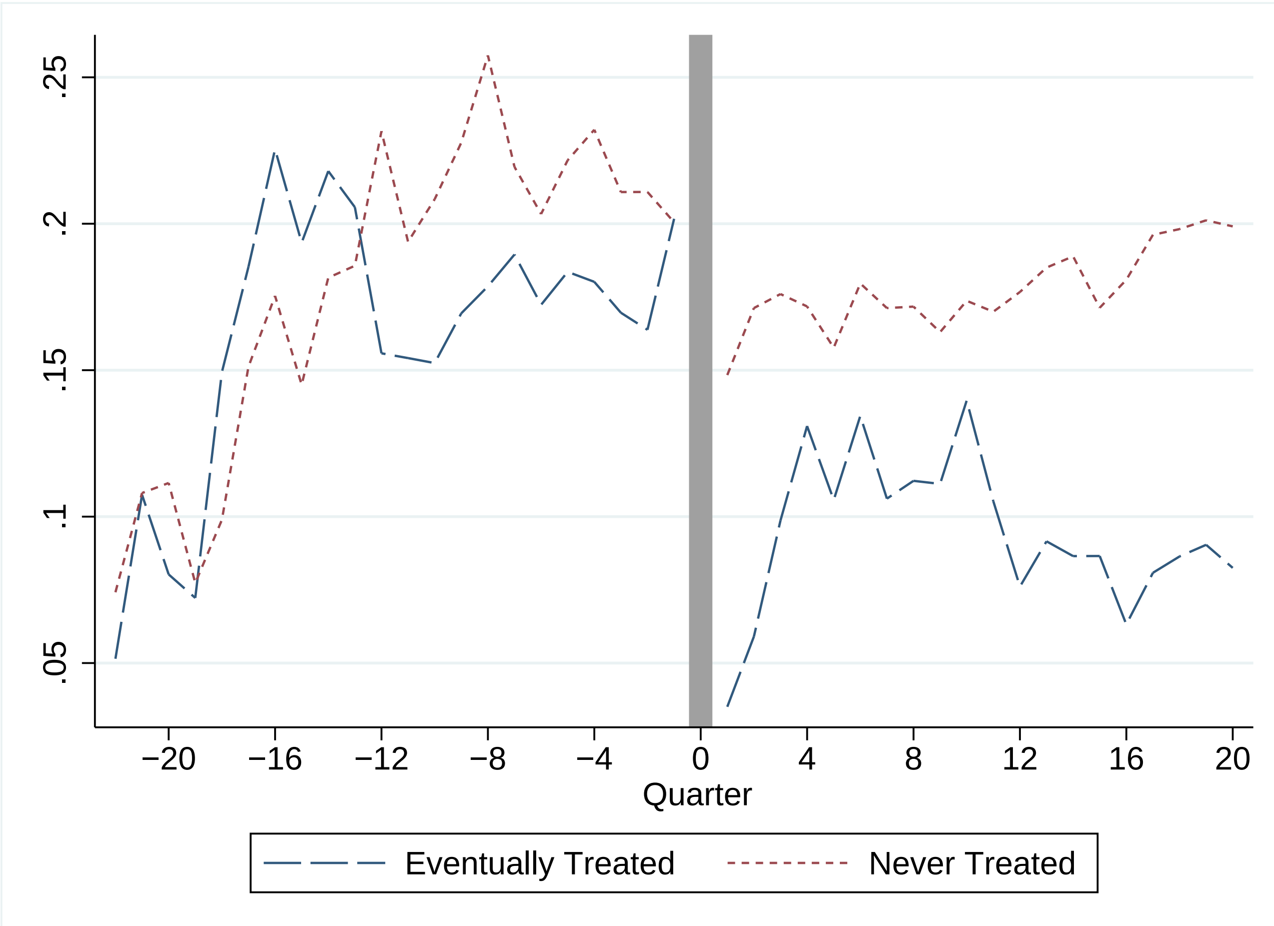
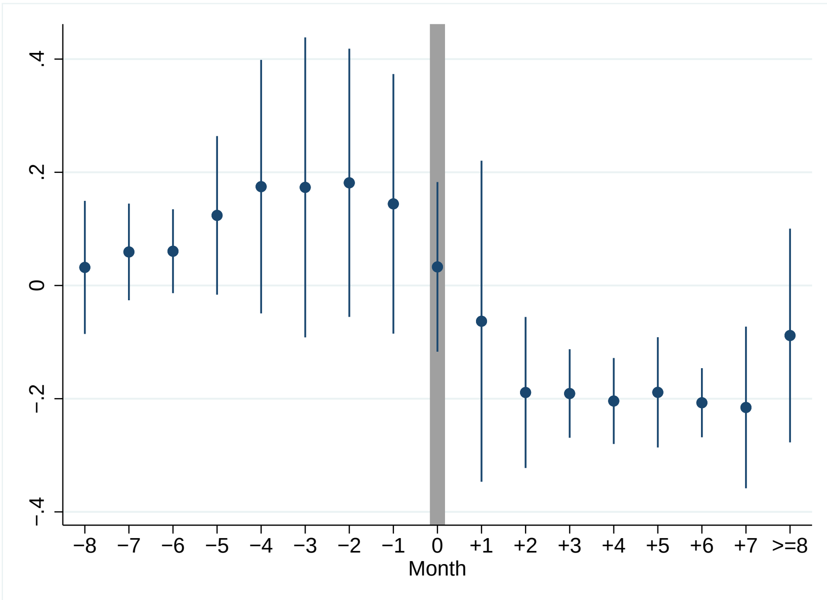


Figure 4: Prices and Profit Margins

Panel A plots the beta coefficients of the regression in equation 1 with the *Post-Treated-Product* dummy split into dummies equal to one for treated products eigth month before and after the event. Panel B plots the beta coefficients of the regression in equation 2 with the *Post* dummy replaced by eight year-quarter dummies before and after the event. The blue lines represent the 95% confidence intervals.

A. Log(Price-Index)



B. Profit Margin

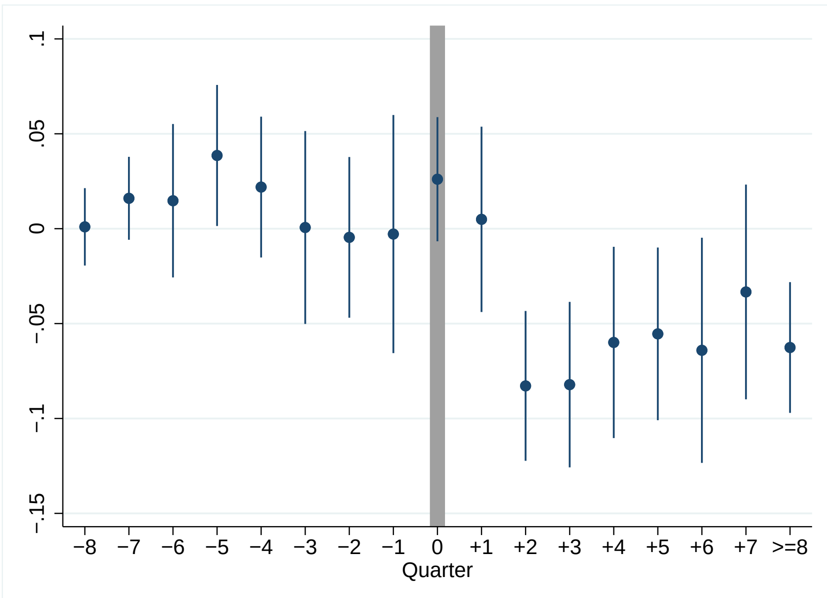
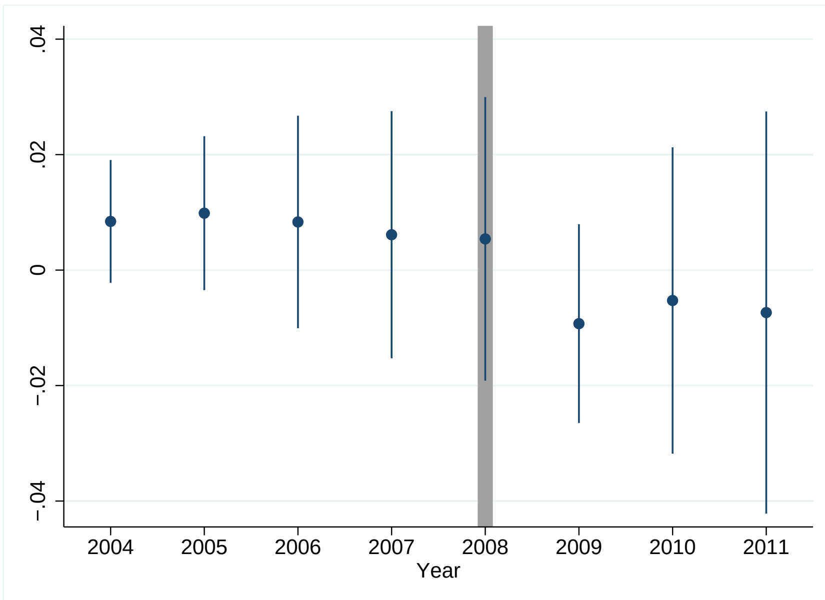


Figure 5: Customer Cost and Cost Dispersion

Panel A plots the difference in material costs between treated and control customers. Treated (control) customers are above (below) the median of the fraction of treated steel material out of total steel material. Panel B plots the difference in COGS/Sales dispersion between treated and control customers. Treated (control) customers are above (below) the median of the fraction of treated steel input out of total steel input. The blue lines represent the 95% confidence intervals.

A. Log(Material Prices)



B. CV(COGS/Sales)

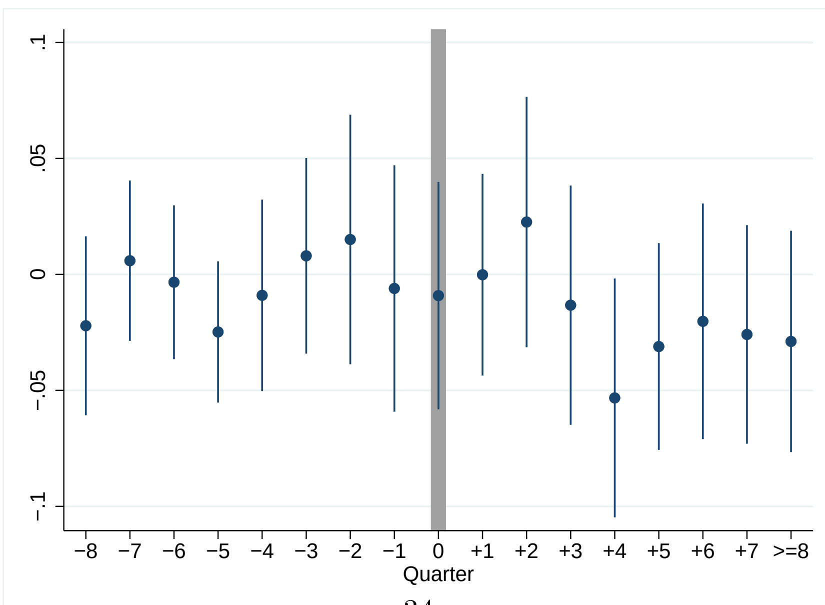
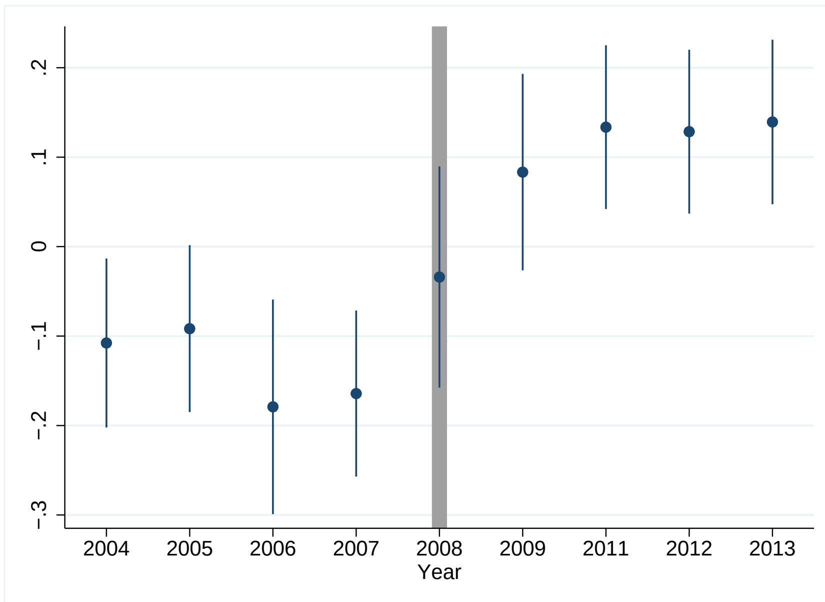


Figure 6: Low-Cost Producer Market Share and Aggregate Producer Productivity

Panel A plots the beta coefficients of the regression in equation 6 and Panel B of the regression in equation 7 with the *Post* dummy replaced by the full set of year dummies. The blue lines represent the 95% confidence intervals.

A. Low-Cost Producer Market Share



B. Log(TFP)

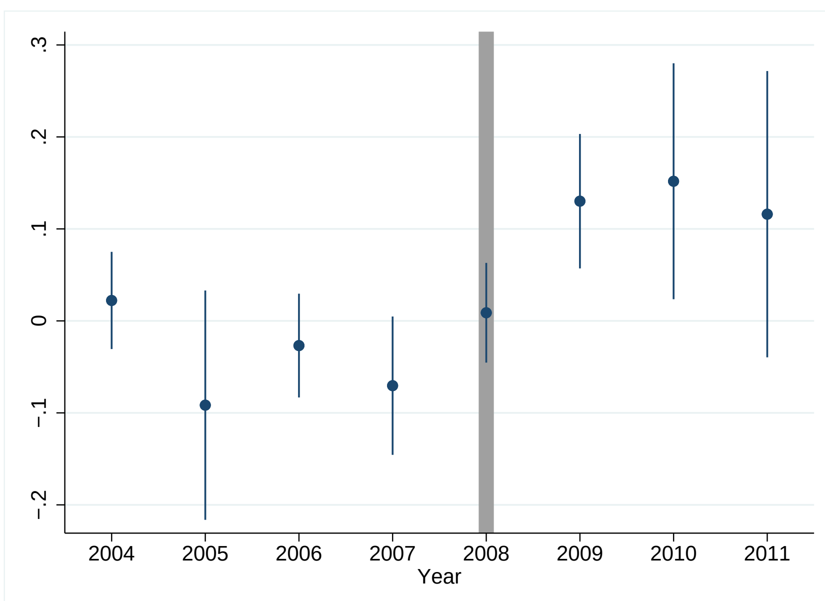


Figure 7: Producer Leverage

This figure plots the beta coefficients of the regression in equation 2 with leverage as the outcome variable and the *Post* dummy replaced by eight year-quarter dummies before and after the introduction of steel futures. The blue lines represent the 95% confidence intervals.

Debt/Assets

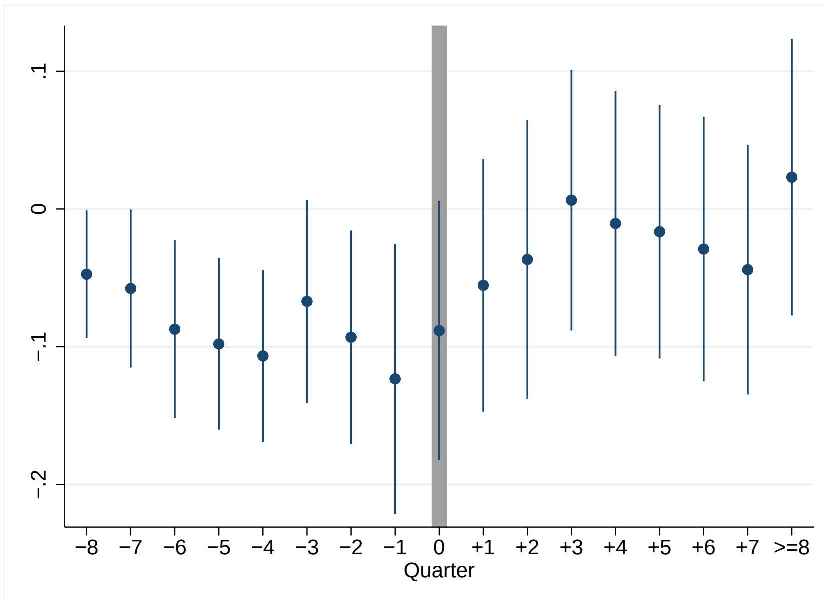


Table 1: U.S. Steel Production by Product

Product	NAICS Product Code	Treatment	% Production
Ingots and semi-finished products[1]	3311113	treated Q2 2008	7
Hot-rolled sheet	3311115	treated Q4 2008	31
Hot-rolled bars	3311117	control	22
Pipes and tubes	3312100	control	6
Cold-rolled sheet	3312211	control	23
Cold-finished bars	3312213	control	2
Wire	3312225	control	2
Other	3321111[2], 3321140[3]	control	6

Source: Adapted from Collard-Wexler and De Loecker (2015).
[1]Including billets. [2]Forgings. [3]Roll form products.

Table 2: Summary Statistics

This table presents summary statistics. Panel A compares firm-level statistics from Compustat for 41 steel producers in the eventually treated industry (NAICS 331111), and 29 steel producers in the never treated industries in 2002. Panel B compares industry-level statistics from the NBER-CES manufacturing database for 53 six-digit steel customer industries with the fraction of treated steel inputs over total steel inputs, Future-Steel, above the median to the remaining 55 steel customer industries. Panel C presents statistics for the main variables in the sample period. The sample period is 2003 to 2013 for all variables except aggregate TFP and Customer Log(Material Prices), which are only available until 2011.

Panel A: Pre-Period Statistics (2002): Producer

	Eventually Treated			Never Treated		
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Profit Margin	140	0.07	0.11	96	0.05	0.10
Assets	140	2,375	2,671	96	635	1,155
Debt/Assets	140	0.29	0.16	96	0.31	0.22
Sales/Assets	140	0.27	0.12	96	0.30	0.11

Panel B: Pre-Period Statistics (2002): Customer

	Future-Steel > Median			Future-Steel ≤ Median		
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Capital	53	2,247	1,798	55	4,064	4,875
Sales/Capital	53	2.66	1.27	55	2.22	0.91

Panel C: Sample Period Statistics:

Variable	Obs.	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
Log(Price-Index)	1188	5.13	0.27	4.56	4.95	5.09	5.31	5.64
Producer Profit Margin	1761	0.11	0.10	-0.25	0.06	0.10	0.17	0.42
Low-Cost Producer Market Share	88	0.42	0.23	0.07	0.22	0.51	0.65	0.67
Aggregate Producer TFP	117	1.00	0.13	0.72	0.91	1.00	1.07	1.30
Steel-Material	972	0.26	0.10	0.14	0.19	0.22	0.28	0.68
Future-Steel-Material	972	0.16	0.08	0.04	0.10	0.12	0.19	0.37
Customer Log(Material Prices)	972	0.17	0.13	-0.21	0.07	0.17	0.26	0.62
Steel-Input	660	0.16	0.04	0.11	0.13	0.15	0.19	0.26
Future-Steel-Input	660	0.11	0.05	0.03	0.07	0.10	0.16	0.22
Customer CV(COGS/Sales)	660	0.15	0.05	0.05	0.11	0.14	0.18	0.44

Table 3: Effect of Steel Futures on Steel Product Prices

This table presents difference-in-differences estimates of the effect of the introduction of steel futures on product-level prices. Product prices are obtained from the BLS Producer Price Index series. Post-Treated-Product is a dummy equal to 1 for treated products after the treatment date. The treatment date is April 2008 for billets and October 2008 for hot-rolled coils. Initial controls include a product's price beta with respect to real GDP and with respect to the construction sector. Crisis controls include interactions of the treatment dummy with real GDP growth and with growth in construction sector employment. Import controls include interactions of the treatment dummy with the log of steel imports and the log of steel imports from China. The sample period is 2003 to 2013. In columnns 1 and 2 the sample is restricted to steel mills. Standard errors are clustered by year-month in columns 1 and 2 and twoway clustered by industry and year-month in columns 3 to 5. *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Log(Price-Index)				
Post-Treated-Product	-0.099***	-0.087***	-0.092***	-0.095***	-0.071**
	(-9.62)	(-2.81)	(-7.14)	(-6.73)	(-3.48)
Post×Initial Controls	No	No	Yes	Yes	Yes
Product×Trend	No	Yes	No	No	Yes
Crisis Controls	No	No	No	Yes	Yes
Import Controls	No	No	No	No	Yes
Product FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Steel Industries	Mills	Mills	All	All	All
R^2	0.915	0.950	0.923	0.923	0.953
Observations	396	396	1,188	1,188	1,188

Table 4: Effect of Steel Futures on Steel Producer Profit Margins

This table presents difference-in-differences estimates of the effect of the introduction of steel futures on gross profit margins. Profit margin is defined as operating income over sales. Treated is a dummy equal to 1 for the treated steel producing industry (NAICS 331111). Post is a dummy equal to 1 after the first steel futures are introduced in Q2 2008. Initial controls include the log of assets, leverage and sales-to-assets measured in 2002, as well as a firm's beta with respect to real GDP and with respect to the construction sector. Crisis controls include interactions of the treatment dummy with real GDP growth and with growth in construction sector employment. Import controls include interactions of the treatment dummy with the log of steel imports and the log of steel imports from China. Industries are defined at the six-digit NAICS code level. The sample period is 2003 to 2013. Standard errors are twoway clustered by industry and year-quarter. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Profit Margin					
Post×Treated	-0.047***	-0.051**	-0.067***	-0.094***	-0.066***	-0.077***
	(-4.00)	(-2.92)	(-3.41)	(-3.76)	(-3.28)	(-3.77)
Post×Initial Controls	No	Yes	Yes	Yes	Yes	Yes
Industry×Trend	No	No	No	Yes	No	No
Crisis Controls	No	No	No	No	Yes	Yes
Import Controls	No	No	No	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	NAFTA	NAFTA	NAFTA	NAFTA
R^2	0.560	0.587	0.531	0.545	0.531	0.544
Observations	1,761	1,761	1,474	1,474	1,474	1,474

Table 5: Effect of Steel Futures on Steel Customer Material Costs

This table presents difference-in-differences estimates of the effect of the introduction of steel futures on steel customer material costs. Steel-Material is the fraction of steel materials out of total materials. Future-Steel-Material is the fraction of treated steel materials out of total materials. The sample is restricted to industries with at least ten percent steel materials and excludes steel producers. Post is a dummy equal to 1 after steel futures are introduced in 2008. Initial controls include the log of capital and sales-to-capital measured in 2002. Crisis controls include interactions of Future-Steel-Material with real GDP growth and with growth in construction sector employment. Import controls include interactions of Future-Steel-Material with the log of steel imports and the log of steel imports from China. Industries are defined at the six-digit NAICS code level. The sample period is 2003 to 2011. Standard errors are clustered by industry. *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Log(Material Prices)		
Post×Future-Steel-Material	-0.101**	-0.101**	-0.100**
	(-2.55)	(-2.42)	(-2.54)
Post×Inital Controls	No	Yes	Yes
Crisis Controls	No	No	Yes
Import Controls	No	No	Yes
Post×Steel-Material	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.959	0.959	0.964
Observations	972	972	972

Table 6: Effect of Steel Futures on Steel Customer Cost Dispersion

This table presents difference-in-differences estimates of the effect of the introduction of steel futures on steel customer cost dispersion. Cost dispersion is measured as the coefficient of variation (standard deviation scaled by mean) of COGS/Sales within four-digit industries. Steel-Input is the fraction of steel inputs out of total inputs. Future-Steel-Input is the fraction of treated steel inputs out of total inputs. The sample is restricted to industries with at least ten percent steel inputs and excludes steel producers. Post is a dummy equal to 1 after the first steel futures are introduced in Q2 2008. Crisis controls include interactions of Future-Steel-Input with real GDP growth and with growth in construction sector employment. Import controls include interactions of Future-Steel-Input with the log of steel imports and the log of steel imports from China. Industries are defined at the four-digit NAICS code level. The sample period is 2003 to 2013. Standard errors are twoway clustered by industry and year-quarter. *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	CV(COGS/Salses)		
Post×Future-Steel-Input	-0.330**	-0.526***	-0.588***
	(-2.30)	(-5.55)	(-3.82)
Post×Initial Controls	No	No	Yes
Industry×Trend	No	Yes	No
Crisis Controls	No	No	Yes
Import Controls	No	No	Yes
Post×Steel-Input	No	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes
R^2	0.340	0.429	0.401
Observations	660	660	660

Table 7: Effect of Steel Futures on Low-Cost Producer Market Share

This table presents difference-in-differences estimates of the effect of the introduction of steel futures on low-cost producer market share. Low-Cost Producer Market Share is the fraction of low-cost producer sales out of total sales in the treatment and control group respectively. Low-cost producer are firms that report operating electric arc furnaces in their 10-K filings in 2002. Treated is a dummy equal to 1 for the treated steel producing industry (NAICS 331111). Post is a dummy equal to 1 after the first steel futures are introduced in Q2 2008. Crisis controls include interactions of the treatment dummy with real GDP growth and with growth in construction sector employment. Import controls include interactions of the treatment dummy with the log of steel imports and the log of steel imports from China. The sample period is 2003 to 2013. Standard errors are clustered by year-quarter. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Low-Cost Producer Market Share			
Post×Treated	0.238***	0.206***	0.259***	0.201***
	(15.04)	(4.67)	(14.66)	(3.51)
Treated×Trend	No	Yes	No	No
Crisis Controls	No	No	Yes	Yes
Import Controls	No	No	No	Yes
Treatment Group FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R^2	0.988	0.988	0.990	0.990
Observations	88	88	88	88

Table 8: Effect of Steel Futures on Aggregate Producer Productivity

This table presents difference-in-differences estimates of the effect of the introduction of steel futures on aggregate producer total factor productivity (TFP). Five-factor industry TFP data are obtained from the NBER-CES manufacturing database. Treated is a dummy equal to 1 for the treated steel producing industry. Post is a dummy equal to 1 after the first steel futures are introduced in Q2 2008. Crisis controls include interactions of the treatment dummy with real GDP growth and with growth in construction sector employment. Import controls include interactions of the treatment dummy with the log of steel imports and the log of steel imports from China. Industries are defined at the six-digit NAICS code level. The sample period is 2003 to 2011. Standard errors are twoway clustered by industry and year. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Log(TFP)		
Post-Treated	0.079**	0.081***	0.082***
	(2.70)	(4.02)	(9.11)
Crisis Controls	No	Yes	Yes
Import Controls	No	Yes	Yes
Treatment	6-digit	6-digit	4-digit
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
R^2	0.733	0.734	0.784
Observations	117	117	117

Appendix to

“Real Effects of Price Transparency: Evidence from Steel Futures”

Table A.1: Anecdotal evidence

A. Physical delivery

In reality, physical delivery occurs in a very small percentage of cases on the LME as most organizations use the exchange for hedging purposes.
Futures Industry, 2011.

B. Choice of products and regional segmentation

Establishing a global price for steel has been met with skepticism by some industry participants because of regional differences between products. [...] Establishing a global price would depend on the product. Maybe a global price for scrap might make sense. **But the price difference between Asia and the U.S. is pretty significant in hot rolled.**
American Metal Market, 2007.

One key characteristic about Shanghais steel futures market is that it is only open to Chinese investors, with all delivery points located in China. Until this market is open to foreign investors, there is little way global steel market participants can use this contract as a hedging tool.
Futures Industry, 2011.

C. Price transparency

Steel futures will allow the financial markets to set steel prices rather than steel mills.
Dan DiMicco, CEO Nucor Corp., the largest steel producer in the U.S.
American Metal Market, 2007.

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.**
Steel Market Update.

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. But that's not specific to the steel industry. In almost every case in the last 30 to 40 years established players have generally resisted new contracts.
Paul Shellman, CME Group
American Metal Market, 2008.

Table A.2: Trading Volume

This table presents the combined trading volume at the LME and NYMEX along with average open interest and U.S. steel production volumes in million ton.

Year	Volume (contracts)	Volume (m. ton)	Production (m. ton)	Volume (% of Production)	Av. Open Interest (m. ton)
2008	3,364	0.22	92	0.24	0.01
2009	15,315	0.45	59	0.75	0.05
2010	37,357	1.54	81	1.90	0.11
2011	43,970	1.62	86	1.89	0.11
2012	60,103	2.14	89	2.40	0.15
2013	65,314	2.00	87	2.30	0.14
2014	45,657	0.93	88	1.05	0.17
2015	58,967	1.18	79	1.49	0.42

Source: Bloomberg and U.S. Geological Survey.

Table A.3: Customer Profit Margins

This table presents difference-in-differences estimates of the effect of the introduction of steel futures on customer profit margins. Profit Margin is defined as sales less payroll, material and energy costs over sales. Steel-Material is the fraction of steel materials out of total materials. Future-Steel-Material is the fraction of treated steel materials out of total materials. The sample is restricted to industries with at least ten percent steel materials and excludes steel producers. Post is a dummy equal to 1 after steel futures are introduced in 2008. Initial controls include the log of capital and sales-to-capital measured in 2002. Crisis controls include interactions of Future-Steel-Material with real GDP growth and with growth in construction sector employment. Import controls include interactions of Future-Steel-Material with the log of steel imports and the log of steel imports from China. Industries are defined at the six-digit NAICS code level. The sample period is 2003 to 2011. Standard errors are clustered by industry. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Profit Margin		
Post×Future-Steel-Material	0.052	0.062	0.066
	(0.61)	(0.70)	(0.85)
Post×Steel-Material	-0.021	-0.032	-0.032
	(-0.61)	(-0.79)	(-0.78)
Post×Inital Controls	No	Yes	Yes
Crisis Controls	No	No	Yes
Import Controls	No	No	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.728	0.729	0.730
Observations	972	972	972

Table A.4: Persistence of the Effect after Recovery

This table presents difference-in-differences estimates of the effect of the introduction of steel futures on gross profit margins. Profit margin is defined as operating income over sales. Treated is a dummy equal to 1 for the treated steel producing industry (NAICS 331111). Post is a dummy equal to 1 after the first steel futures are introduced in Q2 2008. Post-Recovery is a dummy equal to 1 after the steel industry recovered in 2012. Initial controls include the log of assets, leverage and sales-to-assets measured in 2002, as well as a firm's beta with respect to real GDP and with respect to the construction sector. Crisis controls include interactions of the treatment dummy with real GDP growth and with growth in construction sector employment. Import controls include interactions of the treatment dummy with the log of steel imports and the log of steel imports from China. Industries are defined at the six-digit NAICS code level. The sample period is 2003 to 2013. Standard errors are twoway clustered by industry and year-quarter. *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Profit Margin				
Post×Treated	-0.031**	-0.065***	-0.061**	-0.077***	-0.055*
	(-2.58)	(-3.26)	(-2.96)	(-3.74)	(-1.97)
Post-Recovery× Treated	-0.018*	-0.013	-0.018	-0.000	0.020
	(-2.11)	(-1.56)	(-1.48)	(-0.02)	(1.07)
Post×Initial Controls	No	Yes	Yes	Yes	Yes
Industry×Trend	No	No	No	No	Yes
Crisis Controls	No	No	No	Yes	Yes
Import Controls	No	No	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
R^2	0.495	0.531	0.531	0.544	0.556
Observations	1,474	1,474	1,474	1,474	1,474

Table A.5: Effect of Steel Futures on Scale of Operations

This table presents difference-in-differences estimates of the effect of the introduction of steel futures on the scale of operations. Treated is a dummy equal to 1 for the treated steel producing industry (NAICS 331111). Post is a dummy equal to 1 after the first steel futures are introduced in Q2 2008. Initial controls include the log of assets, leverage and sales-to-assets measured in 2002, as well as a firm's beta with respect to real GDP and with respect to the construction sector. Crisis controls include interactions of the treatment dummy with real GDP growth and with growth in construction sector employment. Import controls include interactions of the treatment dummy with the log of steel imports and the log of steel imports from China. Industries are defined at the six-digit NAICS code level. The sample period is 2003 to 2013. Standard errors are twoway clustered by industry and year-quarter. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Log(Assets)	Log(Sales)	Log(Volumes)	Log(Capex)
Post×Treated	0.083	0.083	0.033	-0.002
	(0.45)	(0.39)	(0.18)	(-0.01)
Post×Initial Controls	Yes	Yes	Yes	Yes
Crisis Controls	Yes	Yes	Yes	Yes
Import Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	No
Year FE	No	No	No	Yes
R^2	0.977	0.970	0.977	0.940
Observations	1,463	1,474	1,267	354

Table A.6: Differences in Sensitivity to GDP and Construction Sector

This table presents estimates of steel producers' exposure to real GDP and the construction sector. The betas are obtained from quarterly regressions of a firm's profit margin on log of real GDP and log of construction sector employment respectively, in the period from 1998 to 2007. Treated is a dummy equal to 1 for the treated steel producing industry (NAICS 331111). Initial controls are measured in 2002 and include the log of assets, leverage and sales-to-assets. Industries are defined at the six-digit NAICS code level. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	β_{GDP}		$\beta_{Construction}$	
Treated	-0.186	-0.185	-0.066	0.067
	(-1.20)	(-1.02)	(-0.30)	(0.26)
Initial Controls	No	Yes	No	Yes
R^2	0.022	0.047	0.001	0.019
Observations	67	67	67	67

Table A.7: Placebo Test Around 2001 Recession

This table presents placebo tests around the recession in 2001. Profit margin is defined as operating income over sales. Treated is a dummy equal to 1 for the treated steel producing industry (NAICS 331111). Post is a dummy equal to 1 after Q3 2001. Initial controls include the log of assets, leverage and sales-to-assets measured in 1995, as well as a firm's beta with respect to real GDP and with respect to the construction sector. Crisis controls include interactions of the treatment dummy with real GDP growth and with growth in construction sector employment. Import controls include interactions of the treatment dummy with the log of steel imports and the log of steel imports from China. Industries are defined at the six-digit NAICS code level. The sample period is 1996 to 2006. Standard errors are twoway clustered by industry and year-quarter. *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Profit Margin				
Post×Treated	0.006	0.009	0.008	0.026	0.022
	(0.58)	(0.99)	(0.87)	(1.04)	(1.00)
Post×Inital Controls	No	Yes	Yes	Yes	Yes
Industry×Trend	No	No	No	No	Yes
Crisis Controls	No	No	No	Yes	Yes
Import Controls	No	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Sample	All	All	NAFTA	NAFTA	NAFTA
R^2	0.588	0.616	0.602	0.619	0.626
Observations	1,816	1,816	1,764	1,764	1,764

Table A.8: Changes in Import Competition for Treated and Control Industries

This table presents estimates of changes in import competition around the introduction of steel futures for treated and control industries. % Imports are industry imports scaled by total steel output. Treated is a dummy equal to 1 for the treated steel producing industry (NAICS 331111). Post is a dummy equal to 1 after 2008. Industries are defined at the six-digit NAICS code level. The sample period is 2003 to 2012, as import data not available after 2012 for three of the sample industries. Standard errors are twoway clustered by industry and year. *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	log(Imports)		% Imports	
Post×Treated	-0.033	-0.441	-0.764	-0.780*
	(-0.40)	(-1.04)	(-0.82)	(-2.73)
Exporter Country	All	China	All	China
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.989	0.920	0.976	0.786
Observations	50	50	50	50

Table A.9: Stock Market Reactions

This table presents OLS regressions of the difference in portfolio returns of treated and control firms on dummies for the announcement days for the introduction of steel futures by the LME and NYMEX. Treatment and control group are adapted to the respective announcement. In column (1) treated firms are all firms in steel producing industries as the LME did not specify the affected products initially. The control group are firms in other metal producing industries (NAICS 331 and 332). In column (2) treated firms are hot-rolled coil producers and the control group are all other steel producers. In column (3) treated firms are all firms in steel buying industries with steel inputs above the median. The control group are firms in the other steel buying industries with at least ten percent steel inputs. In column (4) treated firms are all firms in steel buying industries with the fraction of treated steel inputs out of total steel inputs above the median and the control firms are all firms in the other steel buying industries. Announcement LME is a dummy for April 2, 2003, the day the LME first announced their plans to launch steel futures. Announcement NYMEX is a dummy for September 24, 2008, the day the NYMEX announced their plans to launch hot-rolled coil futures. Industries are defined at the six-digit NAICS code level. The sample period is 2002 to 2009. Standard errors are robust to heteroskedasticity. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Return (Treated) – Return (Control)			
Announcement LME	-0.018***		0.004***	
	(-19.22)		(5.71)	
Announcement NYMEX		-0.038***		0.008***
		(-28.34)		(16.20)
Treated	Steel Prod.	Coil Prod.	Steel Cust.	Coil Cust.
Fama-French Factors	Yes	Yes	Yes	Yes
R^2	0.084	0.058	0.045	0.067
Observations	2,015	2,015	2,015	2,015

Table A.10: Treatment Refinement Prices

This table presents difference-in-differences estimates of the effect of the introduction of steel futures on gross profit margins. Profit margin is defined as operating income over sales. The assignment into treatment is refined using a firm's quarterly sales beta with respect to billet and hot-rolled coil prices. Firms in the treated industry (NAICS 331111) with a sales beta with respect to billet (hot-rolled coil) prices above the median are defined as billet (hot-rolled coil) producers. Post-Treated is a dummy equal to 1 for treated firms after the treatment date. The treatment date is Q2 2008 for billet producers and Q4 2008 for hot-rolled coil producers. Initial controls include the log of assets, leverage and sales-to-assets measured in 2002, as well as a firm's beta with respect to GDP and with respect to the construction sector. Crisis controls include interactions of the treatment dummy with real GDP growth and with growth in construction sector employment. Import controls include interactions of the treatment dummy with the log of steel imports and the log of steel imports from China. Industries are defined at the six-digit NAICS code level. The sample period is 2003 to 2013. Standard errors are twoway clustered by industry and year-quarter. *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Profit Margin					
Post-Treated	-0.071***	-0.063***	-0.068***	-0.073***	-0.066***	-0.061***
	(-6.75)	(-5.93)	(-4.71)	(-4.53)	(-4.93)	(-5.64)
Post×Inital Controls	No	Yes	Yes	Yes	Yes	Yes
Industry×Trend	No	No	No	Yes	No	No
Crisis Controls	No	No	No	No	Yes	Yes
Import Controls	No	No	No	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	NAFTA	NAFTA	NAFTA	NAFTA
R^2	0.573	0.595	0.537	0.549	0.537	0.550
Observations	1,761	1,761	1,474	1,474	1,474	1,474

Table A.11: Treatment Refinement 10-K filings

This table presents difference-in-differences estimates of the effect of the introduction of steel futures on gross profit margins. Profit margin is defined as operating income over sales. The assignment into treatment is refined using firms' 10-K filings. Firms in the treated industry (NAICS 331111) which mention billets (hot-rolled coils) in their 2002 10-K are defined as billet (hot-rolled coil) producers. Post-Treated is a dummy equal to 1 for treated firms after the treatment date. The treatment date is Q2 2008 for billet producers and Q4 2008 for hot-rolled coil producers. Initial controls include the log of assets, leverage and sales-to-assets measured in 2002, as well as a firm's beta with respect to GDP and with respect to the construction sector. Crisis controls include interactions of the treatment dummy with real GDP growth and with growth in construction sector employment. Import controls include interactions of the treatment dummy with the log of steel imports and the log of steel imports from China. Industries are defined at the six-digit NAICS code level. The sample period is 2003 to 2013. Standard errors are twoway clustered by industry and year-quarter. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Profit Margin				
Post-Treated	-0.037***	-0.042***	-0.065***	-0.039***	-0.032***
	(-3.91)	(-3.23)	(-6.59)	(-3.62)	(-5.20)
Post×Inital Controls	No	Yes	Yes	Yes	Yes
Industry×Trend	No	No	Yes	No	No
Crisis Controls	No	No	No	Yes	Yes
Import Controls	No	No	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
R^2	0.589	0.609	0.641	0.611	0.632
Observations	1,064	1,064	1,064	1,064	1,064

Table A.12: Producer Leverage

This table presents difference-in-differences estimates of the effect of the introduction of steel futures on leverage ratios. Leverage ratios are computed using the market value of assets. The results are robust to using book values instead. Treated is a dummy equal to 1 for the treated steel producing industry (NAICS 331111). Post is a dummy equal to 1 after the first steel futures are introduced in Q2 2008. Initial controls include the log of assets, leverage and sales-to-assets measured in 2002, as well as a firm's beta with respect to real GDP and with respect to the construction sector. Import controls include interactions of the treatment dummy with the log of steel imports and the log of steel imports from China. Industries are defined at the six-digit NAICS code level. The sample period is 2003 to 2013. Standard errors are twoway clustered by industry and year-quarter. *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Debt/Assets				
Post×Treated	0.093**	0.144**	0.111**	0.123**	0.117*
	(2.75)	(2.49)	(2.81)	(2.59)	(1.81)
Post×Initial Controls	Yes	Yes	Yes	Yes	Yes
Industry×Trend	No	Yes	No	No	No
Crisis Controls	No	No	No	No	Yes
Import Controls	No	No	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Headquarter	All	All	NAFTA	NAFTA	NAFTA
R^2	0.804	0.819	0.823	0.823	0.831
Observations	1,565	1,565	1,317	1,317	1,317

Table A.13: Market Share Sensitivity to Productivity

This table presents difference-in-differences estimates of the effect of the introduction of steel futures on the sensitivity of market share to productivity. The variable Market Share is defined as a firm's sales over steel industry sales in a given year-quarter. In column (1) Productivity is a dummy equal to one for firms reporting operating an electric arc furnace (EAF) in their 2002 10-K filing. In column (2) Productivity is a firm's profit margin in 2002. Treated is a dummy equal to 1 for the treated steel producing industry (NAICS 331111). Post is a dummy equal to 1 after the first steel futures are introduced in Q2 2008. Industries are defined at the six-digit NAICS code level. The sample period is 2003 to 2013. Standard errors are twoway clustered by industry and year-quarter. *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Market Share	
Post×Treated×Productivity	0.005**	0.088***
	(2.80)	(12.35)
Post×Treated	-0.004**	0.001
	(-2.51)	(0.41)
Post×Productivity	-0.002	0.000
	(-1.05)	(0.03)
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Productivity Measure	EAF	Margin
R^2	0.956	0.824
Observations	1,064	1,696

Table A.14: Hedging Probability

This table presents difference-in-differences estimates of the effect of the introduction of steel futures on the probability to hedge. The variable Hedging Dummy is equal to 1 if a firm reports derivative income or losses in a given year-quarter. Treated is a dummy equal to 1 for the treated steel producing industry (NAICS 331111). Post is a dummy equal to 1 after the first steel futures are introduced in Q2 2008. Initial controls include the log of assets, leverage and sales-to-assets measured in 2002, as well as a firm's beta with respect to real GDP and with respect to the construction sector. Crisis controls include interactions of the treatment dummy with real GDP growth and with growth in construction sector employment. Import controls include interactions of the treatment dummy with the log of steel imports and the log of steel imports from China. Industries are defined at the six-digit NAICS code level. The sample period is 2003 to 2013. Standard errors are twoway clustered by industry and year-quarter. *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Hedging Dummy					
Post×Treated	0.058	-0.050	0.020	0.038	-0.000	0.011
	(0.79)	(-0.38)	(0.19)	(0.32)	(-0.00)	(0.11)
Post×Inital Controls	No	Yes	Yes	Yes	Yes	Yes
Industry×Trend	No	No	No	Yes	No	No
Crisis Controls	No	No	No	No	Yes	Yes
Import Controls	No	No	No	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	NAFTA	NAFTA	NAFTA	NAFTA
R^2	0.646	0.652	0.688	0.704	0.688	0.689
Observations	1,761	1,761	1,474	1,474	1,474	1,474

Table A.15: Insurance Provider

This table presents difference-in-differences estimates of the effect of the introduction of steel futures on gross profit margins. The variable Cost-Beta is the beta of firms' sales with a cost index of iron ore and steel scrap prices. Treated is a dummy equal to 1 for the treated steel producing industry (NAICS 331111). Post is a dummy equal to 1 after the first steel futures are introduced in Q2 2008. Initial controls include the log of assets, leverage and sales-to-assets measured in 2002, as well as a firm's beta with respect to real GDP and with respect to the construction sector. Crisis controls include interactions of the treatment dummy with real GDP growth and with growth in construction sector employment. Import controls include interactions of the treatment dummy with the log of steel imports and the log of steel imports from China. Industries are defined at the six-digit NAICS code level. The sample period is 2003 to 2013. Standard errors are twoway clustered by industry and year-quarter. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Profit Margin				
Post×Treated×Cost-Beta	-0.042***	-0.040***	-0.046***	-0.040***	-0.046***
	(-5.19)	(-7.33)	(-6.56)	(-12.93)	(-6.47)
Post×Treated	-0.004	0.013	0.020	-0.016	0.010
	(-0.26)	(1.29)	(1.27)	(-0.93)	(0.62)
Post×Cost-Beta	0.010	0.009	0.010	0.002	0.010
	(1.13)	(1.43)	(1.26)	(0.46)	(1.20)
Post×Inital Controls	No	Yes	Yes	Yes	Yes
Industry×Trend	No	No	No	Yes	No
Crisis Controls	No	No	No	No	Yes
Import Controls	No	No	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Sample	All	All	NAFTA	NAFTA	NAFTA
R^2	0.579	0.588	0.532	0.546	0.545
Observations	1,761	1,761	1,474	1,474	1,474

Table A.16: Standardization

This table presents difference-in-differences estimates of the effect of the introduction of steel futures on product similarity. Product Similarity is the average similarity score of a given producer with its closest rivals using Hoberg and Phillips' (2016) text-based measure of product similarity between firms. Treated is a dummy equal to 1 for the treated steel producing industry (NAICS 331111). Post is a dummy equal to 1 after the first steel futures are introduced in 2008. Initial controls include the log of assets, leverage and sales-to-assets measured in 2002, as well as a firm's beta with respect to real GDP and with respect to the construction sector. Import controls include interactions of the treatment dummy with the log of steel imports and the log of steel imports from China. Industries are defined at the six-digit NAICS code level. The sample period is 2003 to 2013. Standard errors are twoway clustered by industry and year. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Product Similarity					
Post×Treated	0.007	0.001	0.002	0.002	0.003	-0.002
	(1.10)	(0.25)	(0.20)	(0.73)	(0.58)	(-0.41)
Post×Initial Controls	No	No	Yes	No	No	Yes
Industry×Trend	No	Yes	No	No	Yes	No
Import Controls	No	No	Yes	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Rivals	10	10	10	20	20	20
R^2	0.769	0.817	0.786	0.729	0.755	0.739
Observations	230	230	230	230	230	230