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THE REAL IMPACT OF PASSIVE INVESTING IN FINANCIAL MARKETS*

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ABSTRACT

We study the real economic impact of passive investing in financial markets. In 2004, there was a dramatic increase in commodity index investing, an event referred to as the financialization of commodity futures. We quantify the impact of financialization by examining the economic link between commodity futures markets and firms which use commodities as an intermediate good. Using a difference-in-difference analysis, we find that firms which use commodities experience increases in their cost of goods sold and cost of capital, decreases in their cash flows and return on assets, and increased volatility in their stock returns. Consistent with theoretical models in which market participants learn from market prices, our results suggest that passive investing in financial markets distorts the price signal thereby generating significant negative externalities for the real economy.

JEL classification: G12, G14, Q02

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"…these financial markets have developed massively with the arrival of these new financial investors, who are purely interested in the short-term monetary gain and are not really interested in the physical thing – they never actually buy the ton of wheat or maize; they only buy a promise to buy or to sell. The result of this financialization of the commodities market is that the prices of the products respond increasingly to a purely speculative logic. This explains why in very short periods of time we see prices spiking or bubbles exploding, because prices are less and less determined by the real match between supply and demand."

- *Olivier De Schutter, United Nations Special Rapporteur*

Does passive investing in financial markets impact the real economy? In theory, prices aggregate the private signals of market participants thereby revealing information. In that capacity, *informed* trading in financial markets should influence the economic decisions of agents and therefore impact the real economy. But what about passive investing? Is passive investing merely a sideshow which transfers risk and wealth from one trader to another, or does it influence real economic outcomes?

In this paper we present novel evidence that passive investing not only impacts the real economy, but it leads to significant negative externalities because it impedes the ability of agents to extract signals from market prices. To establish this we use the commodity futures market as a laboratory for understanding the impact of passive investing. The commodity futures market experienced a dramatic increase in passive index investment in 2004, an event which is referred to as the "financialization" of commodity markets (e.g., Tang and Xiong (2012), Cheng and Xiong (2014), and Christoffersen and Pan (2014)). We test whether this increase in passive investment feeds back into the real economy. Our results suggest that firms with significant economic exposure to commodities experience degradation in a wide-variety of economic performance measures following the financialization of commodity markets. Thus, passive investing generates significant negative externalities for the real economy.

We use annual reports to create a measure of each firm's economic exposure to the commodity market. Per U.S. Generally Accepted Accounting Principles (GAAP), firms are required to disclose potentially material risks that may impact their business.[1] Accordingly, we calculate each firm's exposure to the commodity market by counting the number of times that exchange listed commodities are mentioned in its annual report (SEC form 10K).

We categorize exchange listed commodities into three groups: Agriculture, Energy, and Metals. We then define a firm as *commodity sensitive* if its word count is in the top decile of all word counts for any of the three commodity groups. Using a difference-in-difference analysis, we find that the financialization of commodity markets leads to significant increases in the volatility of cash flows, cost of goods sold, return on assets, and stock prices. These effects occur for commodity sensitive firms, but not for other firms. We also find increases in the level of cost of goods sold and cost of capital for commodity sensitive firms. Finally, we find that commodity sensitive firms experience decreases in their cash flows and return on assets. The results suggest that passive investing in commodity markets hurts firms which are economically exposed to commodities.

As predicted by theory, we find evidence that passive investing impacts the real economy because it impedes the ability of agents to extract signals from market prices. A number of theoretical models show that passive investing can alter the information in market prices (e.g., Basak and Pavlova (2012), (2015) and Goldstein, Li, and Yang (2014)). Moreover, several models show that managers of firms learn by observing market prices, and as a result, shocks to

[1] For example, SFAS No. 133 requires firms to disclose the fair value of commodity derivatives contracts.

market prices can feed back into the real economy (e.g., Edmans, Goldstein, and Jiang (2015), Sockin and Xiong (2015)). In particular, Sockin and Xiong (2015) show that commodity prices can influence firm production decisions, because prices aggregate signals about future economic conditions. They hypothesize that increased passive investing in commodity markets may impede the ability of firms which *use* commodities as an intermediate good, since these firms use futures prices to extract signals about future economic demand.

To test whether passive investing impacts firm production decisions, we use the Bureau of Economic Analysis "Make and Use" tables to split our sample of *commodity sensitive* firms into those which *use* commodities as an intermediate good, and those which *produce* commodities.[2] Sockin and Xiong (2015) argue that commodity users are more likely than commodity producers to base investment decisions on observed prices. Consistent with this cross-sectional prediction, we find that the real effects of passive investing are concentrated in firms which *use* commodities, but not in firms which *produce* commodities.

As discussed by Bray (1981), market prices can affect asset demand in multiple ways. While models like Edmans, Goldstein, and Jiang (2015) and Sockin and Xiong (2015) highlight the informational role of prices, prices also help determine budget constraints which in-turn impact firm demand. Accordingly, we control for the level of cost of goods sold to account for the direct impact that commodity prices have on the budget constraints of commodity users. Our results persist even after controlling for the budget constraint channel. Overall, the evidence shows that passive investing in commodity markets negatively impacts the real economy because it distorts the information in observed prices.

[2] The "Make and Use" tables are accounting tables designed to measure value added from the production process in order to estimate GDP.

In equilibrium, both trading by investors and firm decisions are co-determined. To estimate the impact of passive investing, we need a source of exogenous variation. We exploit the financialization of the commodity futures market as a source of exogenous variation in passive investing. Our identification assumption implies that, in the absence of financialization, the average change in commodity sensitive firms would have been equal to the average change in the control group. Crucially, we include both firm and time fixed effects, so our results are immune to variation in macro-economic conditions as well as persistent differences between commodity sensitive and non-commodity sensitive firms.

Two concerns could lead to violations of our identification assumptions. The first concern is reverse causality: passive investors could increase their exposure to commodities because of future changes to commodity sensitive firms' financial performance. This seems unlikely in our setting. Stoll and Whaley (2010), Irwin and Sanders (2011), and Boons, de Roon, and Szymanowska (2014) argue that the increase in passive investing was largely due to diversification motives. The second concern is an omitted variable bias: there is an omitted variable which is not absorbed by firm and time fixed effects (i.e., time-varying omitted variable) and is correlated with both financialization and the financial performance of commodity users. To violate our identification assumptions, such a variable would have to be related to financialization and the financial performance of commodity users, but not related to the performance of commodity producers or firms which are not exposed to the commodity market.[3]

We perform a number of checks to assuage concerns of a time-varying omitted variable bias. First, several empirical papers show that financialization primarily impacted index commodities, because the rise in passive investing occurred due to an increase in passive index

[3] Moreover, in unreported results, we find that our findings hold after including industry-quarter fixed effects. Thus, the results are not driven by time-varying changes in industry conditions.

investors (Tang and Xiong (2012), Stoll and Whaley (2010)). In our main analyses we include only commodities that are part of a major index. In robustness checks we explore non-index commodities and find no effects for firms that are exposed to non-index commodities after the 2004 financialization of commodities. The results serve as a placebo test which confirm that our main findings only occur for the expected groups of firms. Second, we apply a placebo test in which we use a randomly chosen date prior to 2004 as the date for financialization. We find no significant results for this sample, which suggests that control firms are a valid counterfactual for commodity sensitive firms, absent financialization.[4] As such, a time-varying omitted variable bias seems unlikely.

Overall, we use the dramatic increase in index investing in the commodity market as a laboratory for understanding the real economic impact of passive investing. The paper makes several contributions. First, the paper adds to the literature on feedback effects by providing novel evidence that managers do extract useful signals from market prices. Second, the paper shows that financial markets are not just a sideshow which transfers risk and wealth from one investor to another. We find that commodity market prices impact firm outcomes, and as a result, financial markets impact the real economy. Third, the paper adds to the growing literature on the relation between commodity markets and equity markets. While several recent papers document increased comovement between commodity index returns and stock index returns, we provide the first direct evidence that commodity market prices impact stock prices directly, via an information channel which feeds back into firm decisions. Finally, the paper provides evidence that passive investing can lead to negative externalities in the real economy.

[4] In Section 4, we also discuss the impact of firm hedging decisions on our results. While some firms do hedge their exposure to commodity prices, most commodity futures contracts have maturities of two years or less. Thus, long term shocks, like financialization, are still relevant even for firms with hedged exposures. Moreover, few firms are able to perfectly hedge their exposure to commodity prices, and existing work finds that most firms do very little hedging (Guay and Kothari (2003)).

The remainder of this paper proceeds as follows: Section 1 describes the existing literature and develops the theoretical motivation, Section 2 reports the data used in this study and discusses the identifying assumptions. Section 3 tests whether passive investing impacts firms. Section 4 provides evidence of the economic channel and performs robustness tests. Section 5 concludes.

1. Theory

There is a recent, and ardently debated, question of whether futures trading affects commodity prices. Opponents argue, as summarized by Sockin and Xiong (2015), that "…as the trading of financial traders in futures markets does not directly affect the supply and demand of physical commodities, there is no need to worry about them affecting commodity prices." However, the model in Sockin and Xiong (2015) shows that speculative trading *does* impact market prices because of the informational role of prices. In fact, a number of theoretical models show that prices contain information about individual investor beliefs. Grossman and Stiglitz (1976) show that market prices aggregate beliefs about the returns to owning an asset. As a result, investors can learn about the future by looking at prices today. Baker, Stein, and Wurgler (2003) show that non-fundamental shocks to stock prices may impact corporate investment decisions and Goldstein and Guembel (2008) show that prices feed back into the real value of the firm, which can create an incentive for uninformed investors to manipulate prices.[5]

Bray (1981) specifically considers the role of futures markets and examines the conditions under which futures prices can be used as a sufficient statistic to estimate spot prices.

[5] Several empirical papers document evidence of feedback effects from market prices to real decisions. For example, Chen, Goldstein, and Jiang (2007) empirically show that managers learn from prices and this impacts corporate investment decisions. Similarly, Edmans, Goldstein, and Jiang (2012) show that exogenous price shocks trigger takeover attempts.

In her model, traders extract signals about the future return to holding an asset by observing the futures price today, and they use this information to make production decisions. More recently, Sockin and Xiong (2015) develop a model that specifically discusses commodity prices. In their model, futures prices for commodities feed back into producers' production decisions and commodity demand. Thus, in contrast to the idea that futures trading does not matter, Sockin and Xiong (2015) argue that futures trading can affect commodity prices and real economic decisions.

In a world without informational frictions, prices only have one effect: higher prices decrease demand (and vice-versa). This effect, which we call the *budget constraint channel*, says that futures prices simply *track* the spot price. In contrast, the Sockin and Xiong (2015) model shows that when informational frictions are introduced, futures market prices can *impact* spot prices. If commodity purchasers use futures prices as a source of information, then a higher futures price can be interpreted as higher future demand for the commodity, implying a need to buy more of the commodity today. Thus, the informational role of prices may lead to the opposite result of the budget constraint channel. In other words, Sockin and Xiong (2015) show that the informational channel can dominate the cost channel, leading to a positive price elasticity of commodity demand by producers.

Several other papers examine feedback effects in which prices impact decision-making. For example, Goldstein, Li, and Yang (2014) model prices in a setting where traders have different trading opportunities and take different informational signals from prices. They show that increased trading, even by informed traders, can reduce price informativeness. Interestingly, this suggests that increased trading may lower the informativeness of prices which can then negatively impact those who rely on prices as a signal about future demand (as in Sockin and Xiong (2015)).

In this paper, we seek to understand the real economic impact of the recent changes to commodity price dynamics. To do this, we focus on a particular link between commodity markets and the economy: firms which either use or produce commodities in the regular course of their business. To motivate our empirical analyses, we develop theoretical predictions using the model in Sockin and Xiong (2015) combined with the assumption that the process of financialization manifests as an upward shift in the mean and variance of the distribution of uninformed trading (the random variable θ in Sockin and Xiong (2015)). In other words, we derive theoretical predictions under the assumption that increased passive trading by index investors allows previously orthogonal financial shocks, like investor diversification needs, to impact commodity prices and as a result, commodity prices are nosier. Applying this assumption to Sockin and Xiong's model of commodity markets yields three testable predictions:

(i) The volatility of total costs increases post-financialization for commodity sensitive firms.

(ii) The volatility of profits increases post-financialization for commodity sensitive firms.

(iii) The volatility of stock returns increases post-financialization for commodity sensitive firms.

However, we do note there is an active debate regarding the precise impact of passive investors on commodity futures prices. Several papers argue that the large increase in passive investing did not significantly alter the level or volatility of prices in the commodity futures market (e.g., Stoll and Whaley (2010), Hamilton and Wu (2015)). On the other hand, several papers document evidence that passive investing does impact commodity prices. Singleton (2015) finds that index investor flows do push oil futures prices. In a related finding, Henderson, Pearson, and Wang (2015) show that *uninformed* flows into commodity-linked notes lead to significant changes in commodity prices. Finally, Cheng, Kirilenko, and Xiong (2015) show that, conditional on fluctuations in the risk absorption capacity of commodity index traders, trading by index traders does impact commodity futures prices. In our context, we stress that our analyses are not dependent on the idea that passive investors change the level or volatility of commodity prices. Rather, our analyses suggest that trading by passive investors allows unrelated shocks, like investor diversification needs, to impact the *information* in commodity prices.

Theoretical Framework

Consider the model presented in the Internet Appendix of Sockin and Xiong (2015) which examines the impact of informational frictions in commodity futures markets on firms which use commodities to produce goods.[6] In what follows, we use this model to derive predictions on how financialization affects the equilibrium volatilities of costs, profits, and firm stock prices for commodity sensitive firms. Our main assumption is that the financialization of commodity markets introduces additional noise trading by uninformed investors.[7] Formally, we assume that financialization leads to an increase in both the mean and variance of the distribution of the parameter $\theta \sim N(\bar{\theta}, \sigma_\theta^2)$, where θ is a measure trading that is unrelated to fundamentals. The effect of financialization on the volatility of a variable y is then given by the differential of *Var(y)* in the direction $h = [d\bar{\theta}, d\sigma_\theta^2]'$:

$$\delta(Var(y); h) = \frac{\partial Var(y)}{\partial \bar{\theta}} d\bar{\theta} + \frac{\partial Var(y)}{\partial \sigma_\theta^2} d\sigma_\theta^2 \tag{1}$$

[6] Sockin and Xiong refer to these firms as "goods producers." In our setting, we refer to them as "commodity users."

[7] This is consistent with the findings of Henderson, Pearson, and Wang (2015) who show that *uninformed* trading led to significant changes in commodity futures prices.

The following two propositions show that the unconditional volatilities of costs and profits increase for goods producing firms post-financialization. We simplify the notation used in Sockin and Xiong (2015) and only describe the signs of coefficients when absolutely necessary. From the model the equilibrium spot prices, P, can be re-written as:

$$logP = \alpha logA + \beta\theta + \gamma\xi + \lambda \tag{2}$$

where $logA$, θ, and ξ are independent normal random variables and $\alpha, \beta > 0, \gamma$, and λ are constants. The variable $logA$ represents global fundamentals (i.e., the strength of the economy which influences global demand) and ξ is a supply shock.

Similarly, the commodity demand for a single firm, X_i, can be re-written by:

$$logX_i = \tilde{\alpha} logA + \tilde{\beta}\theta + \tilde{\gamma}\xi + \tilde{\lambda} \tag{3}$$

Here we are making the explicit assumption that the constant l_p in Sockin and Xiong's model satisfies $l_p > -\frac{l_f}{h_F}$ so that the constant $\tilde{\beta} = \left(l_f \widetilde{h_\theta} + l_p h_F \widetilde{h_\theta}\right) > 0$.[8] We view this assumption as reasonable and necessary to proceed - the sign of l_p is undetermined in the model and varies between positive and negative values depending on the parameters of the model. Total costs are thus given by:

$$Costs_i = X_i P = e^{logX_i} + logP \tag{4}$$

and profits are given by:

$$Profits_i = e^{\eta\phi\, logX_j + \phi\, logX_i} A - Costs_i \tag{5}$$

Volatility of Costs and Revenues for Goods Producers

[8] This assumption can be relaxed if we change our definition of financialization to only affecting the variance of the distribution of θ. In this case, no assumptions need to be made on the signs of any of the undetermined coefficients in Sockin and Xiong's model.

Proposition 1. The unconditional volatility of total costs increases post-financialization for goods producing firms.

Proof. Consider the term $logX_i + logP$. This term can be re-written as $z = alogA + b\theta + c\xi + d$ where $b > 0$. Note that this since this variable is the sum of independent normal random variables, it is a normal random variable itself with distribution $z \sim N(\mu, \sigma^2)$. By the independence of $logA, \theta$, and ξ, we have that the mean and variance are given by:

$$\mu = \alpha\bar{A} + b\bar{\theta} + c\bar{\xi} + d \tag{6}$$

and

$$\sigma^2 = \alpha^2\sigma_A^2 + b^2\sigma_\theta^2 + c^2\sigma_\xi^2. \tag{7}$$

Thus, the variance of the term $Costs_i = e^{z_i}$ is given by:

$$var(Costs_i) = var(e^{z_i}) = e^{2\mu+2\sigma^2} - e^{2\mu+\sigma^2}. \tag{8}$$

Differentiating this term with respect to $var(\theta) = \sigma_\theta^2$ and applying the Chain Rule yields:

$$\frac{\partial var(Costs_i)}{\partial var(\theta)} = 2b^2e^{2\mu+2\sigma^2} - b^2e^{2\mu+\sigma^2} \tag{9}$$

since $\sigma^2 > 0$ we have that $e^{2\mu+2\sigma^2} > e^{2\mu+\sigma^2}$. Moreover, since $b^2 > 0$, we have that $\frac{\partial var(Costs_i)}{\partial var(\theta)}$ > 0. Differentiating the same term with respect to $\bar{\theta}$ and applying the Chain Rule also yields:

$$\frac{\partial var(Costs_i)}{\partial var(\bar{\theta})} = 2be^{2\mu+2\sigma^2} - be^{2\mu+\sigma^2} \tag{10}$$

and since $b > 0$ we have that $\frac{\partial var(Costs_i)}{\partial var(\bar{\theta})} > 0$. Finally, using the definition of financialization we have that:

$$\delta(Var(Costs_i); h) = \frac{\partial var(Costs_i)}{\partial var(\bar{\theta})}d\bar{\theta} + \frac{\partial Var(Costs_i)}{\partial \sigma_\theta^2}d\sigma_\theta^2, \tag{11}$$

as was to be shown. ■

Note that the unconditional volatility of the revenues will increase in this case as well. Without loss of generality, we can write the realized equilibrium revenue of a goods producer as:

$$Revenue_i = Ae^{mlogX_i} \tag{12}$$

Using the same steps as Proposition 1 and realizing that $e^{logA} = A$ we can re-write the revenue function as:

$$var(Revenue_i) = var(e^{\tilde{a}logA+\tilde{b}\theta+\tilde{c}\xi+\tilde{d}}) \tag{13}$$

Define $w = \tilde{a}logA + \tilde{b}\theta + \tilde{c}\xi + \tilde{d}$. Using the same logic as Proposition 1 yields the expression for the volatility of revenue:

$$var(Revenue_i) = var(e^{2\mu_w+2\sigma_w^2} - e^{2\mu_w+\sigma_w^2}). \tag{14}$$

Again, by the positivity of $\tilde{\beta}$ and σ_w^2 we have that differentiation of $var(Revenue_i)$ with respect to $\bar{\theta}$and σ_θ^2 leads to the following result:

$$\delta(Var(Costs_i); h) = \frac{\partial var(Revenues_i)}{\partial var(\bar{\theta})} d\bar{\theta} + \frac{\partial Var(Revenues_i)}{\partial \sigma_\theta^2} d\sigma_\theta^2 > 0. \tag{15}$$

Volatility of Profits for Goods Producers

So far we have shown theoretically that both the volatility of revenues and costs increases for goods producing firms after financialization. The problem we are left with is to examine the effects of financialization on the volatility of profits. To avoid unnecessary complications that arise when dealing with linear combinations of lognormal random variables, we choose to provide only a general sufficient condition under which the volatility of profits increases post-financialization.

Proposition 2 shows that if the random variables that determine revenues and costs satisfy some mild conditions, then the volatility of profits increases post-financialization for commodity sensitive firms.

Proposition 2. Denote $x = \tilde{a}logA + \tilde{b}\theta + \tilde{c}\xi + \tilde{d}, y = z$ so that $x \sim N(\mu_x, \sigma_x^2),\ y \sim N\left(\mu_y, \sigma_y^2\right)$. Suppose also that $\mu_x > \mu_y + \log(4)\,, \sigma_x^2 > \sigma_y^2, and\ \tilde{b} > b$. Then $\delta(Var(Profits); h) > \delta(Var(Costs_i); h) > 0$. Moreover, we have that $\delta(Var(Profits); h) > \delta(Var(Revenues_i); h) > 0$ if $\mu_x + \log(4) < \mu_y\,, \sigma_x^2 < \sigma_y^2, and\ \tilde{b} < b$.

Proof. See Appendix.

Volatility of Returns for Goods Producers

We now show that the volatility of stock returns should increase post-financialization. Since stock prices are not explicitly modelled in Sockin and Xiong (2015), we make the simplifying assumption that the economy ends after the profits stage. Let S_0 be the time 0 stock price summarized by the expected future profits (a constant at time 0). Moreover, the time 1 stock price is simply the profits: $S_1 = Profits$. Gross returns then satisfy the simple ratio $R = \frac{S_1}{S_0}$ and the variance is given by:

$$var(R) = var\left(\frac{S_1}{S_0}\right) = \frac{1}{S_0^2} var(S_1) = \frac{1}{S_0^2} var(Profits) \tag{16}$$

Therefore, as long as we have that $\delta(Var(Profits); h) > 0$, we have that $\delta(Var(R); h) > 0$.

Implementation

We test the three predictions derived above using financial data from Compustat and the Center for Research in Security Prices (CRSP). First, in Sockin and Xiong (2015) costs are modelled as the quantity of commodity inputs multiplied by the unit commodity price. A natural proxy variable for this theoretical construct is raw materials costs. Unfortunately, Compustat does not provide details about costs at this level of granularity. Instead, we adopt *Cost of Goods Sold* (*COGS*) as our proxy for costs and calculate volatility at the annual level using quarterly data. Note that *Cost of Goods Sold* can be decomposed as:

$$Cost\ of\ Goods\ Sold = Raw\ Materials\ Cost + Labor\ and\ Indirect\ Costs \tag{17}$$

Therefore, if we make the assumption that financialization did not affect the volatility of *Labor and Indirect Costs*, then all changes in the volatility of the *Cost of Goods Sold* variable in our difference-in-differences regressions should be attributable to changes in the volatility of *Raw Materials Cost*.

Second, Sockin and Xiong (2015) model profits as total revenues net of input costs. We adopt both *Net Income Before Extraordinary Items* (IBQ) and *Cash Flow* as our proxies for profits (See Table 2 for detailed variable definitions). Again, we calculate volatility at the annual level using quarterly data. The benefit of using *Cash Flows* in addition to *Net Income* is that *Cash Flows* remove the accrual component of earnings, which can be subject to management manipulation. If financialization affected the incentives of management to "smooth earnings," then *Cash Flow* may provide us with a better proxy for economic profits than *Net Income*. On the other hand, as long as financialization does not affect the volatility of the accrual component of *Net Income*, we should arrive at similar conclusions for both *Net Income* and *Cash Flow* in our difference-in-differences regressions.

Third, although Sockin and Xiong (2015) do not explicitly model stock prices, we impose additional assumptions on their model and derive stock price dynamics for commodity sensitive firms. If the stock price is equal to the expected future risk-adjusted cash flows, then the volatility of the stock price is driven by the volatility in cash flows. Thus, given that we expect profits and cash flow volatility to rise post-financialization, we expect the volatility of stock returns to rise as well. We adopt the daily stock return from CRSP as our return variable and calculate volatility at the annual level using the standard deviation of daily return data.

2. Data and Identification Strategy

To test the impact of passive investing we use quarterly and annual data from Compustat and CRSP, as well as SEC filings from the EDGAR database. We study annual firm financial data over the period from 2000 to 2007.[9] This period represents a symmetric eight year window around the date of financialization and avoids contamination by the financial crisis. The sample consists of non-financial firms with non-missing CIK numbers belonging to the intersection of Compustat and CRSP. CIK identifiers are required to match firm-year observations to the SEC annual report data we use to construct the treated sample. Firms with missing values for total assets and firms with total assets less than 10 million are excluded.[10] All outcome variables are winsorized at the 99.9th and 0.1st percentiles.

Treated Sample

Theoretically, Sockin and Xiong (2015) show that financialization affects firms which condition upon commodity prices to make production decisions. Empirically, Tang and Xiong (2012) show that only commodities that belong to a commodity index are affected by

[9] The results are robust to the period starting in 1998 and ending in 2010. The first year that we can access complete SEC FTP data is 1998.
[10] See Chen, Edmans, and Jiang (2007). Most of our variables are financial ratios that use total assets in the denominator. Excluding such firms mitigates outlier observations caused by low levels of total assets.

financialization. Accordingly, motivated by these findings, we define *treatment firms* in our sample as the set of firms who are economically exposed to index-member commodities.[11]

One difficulty that arises is that it is not ex-ante obvious how to identify commodity sensitive firms in the data. Standard Industrial Classification (SIC) codes are not detailed enough to reflect the wide range of business activities for conglomerate firms. Moreover, SIC codes are incapable of identifying the exact set of commodities to which a firm is economically exposed. Similarly, regressions of stock returns on commodity returns are also insufficient for identifying commodity sensitive firms. Coefficient estimates from such regressions are biased towards zero as a consequence of hedging activities and such an analysis requires the additional assumption that stock market participants correctly understand each firm's economic exposure, which may introduce bias into the analysis. Furthermore, such regressions are prone to empirical misspecification errors and do not reflect the economic relation in Sockin and Xiong (2015).

Accordingly, we identify commodity sensitive firms by examining firms' annual reports (10-Ks).[12] Per U.S. GAAP, firms are required to disclose potentially material risks that may impact their business. We calculate each firm's exposure to the commodity market by counting the number of times that exchange listed commodities are mentioned in its annual report. We parse annual report files from the SEC EDGAR server for the commodities mentioned in Table 1.[13] Specifically, we search each annual report for mentions of agricultural, energy, metals, and out-of-index commodities and tabulate the total mentions by commodity group each year. The

[11] The oldest, and perhaps most widely used, commodity index is the Standard and Poor's – Goldman Sachs Commodity index (S&P-GSCI) which was created in 1989. While the weights on each commodity in the index change over time, the commodities in the index have remained relatively constant. Individual contracts regularly roll in and out of the index as futures contracts expire, but each expiring contract is replaced by other outstanding futures contracts on the same commodity. See Stoll and Whaley (2010) for details.
[12] We start our sample in 1998, because it is the first year of complete data in EDGAR.
[13] We drop the metal *lead* from our analysis, since the word *lead* has a commonly used alternate meaning unrelated to commodities.

result of this process is a firm-year panel dataset detailing the number of times agricultural, energy, metals, and out-of-index commodities are mentioned each year for each firm.

Firm-year commodity word counts are then aggregated based on the groupings listed in Table 1, with out-of-index commodities placed into a single group. The Index Commodities include 23 different types: 5 Energy, 12 Agriculture, and 6 Metals. The non-Index Commodities include 10 types: 2 Energy, 4 Agriculture, and 4 Metals. Table 1 lists the exchange on which each commodity is traded.

INSERT TABLE 1 ABOUT HERE

We base our definition of treatment firms using word-counts from 1998 through the year of financialization (2004). Commodity group word counts are then averaged by firm over the period 1998 to 2004 to estimate each firm's exposure to each commodity group. A firm is defined as treated if either (1) its average agricultural word count is in the top decile of average agricultural word counts, (2) its average energy word count is in the top decile of average energy word counts, or (3) its average metal word count is in the top decile of average metal word counts. Average out-of-index word counts are not used to define treatment firms because only in-index commodities are affected by financialization (Tang and Xiong (2012)).

As an illustrative example, consider the confectionery product maker Hershey. Hershey's average commodity group word counts are 55, 2, and 0 for agricultural, energy, and metals commodities, respectively. The 90^{th} percentile average word counts, across all firms, are 5, 12.5, and 4 for agricultural, energy, and metals commodities, respectively. Hershey is therefore defined as a treated firm because its average agricultural word count (55) is in the top decile of average agricultural word counts. Note that even though Hershey's energy and metal word counts are far below the 90th percentile, Hershey is still defined as treated due to its agricultural word count.

We also classify commodity sensitive firms as either a "user" or a "producer" of commodities using BEA input-output data. We define a producer of commodities as a firm whose primary business activity is the production or manufacturing of raw materials up until the point at which they can be traded on a futures exchange. For example, both miners of raw aluminum and manufacturers of refined aluminum are classified as a producer of commodities. A user of commodities is defined as a firm whose primary business activity involves using tradable commodities as a raw input to manufacture finished goods. For example, auto-parts manufacturers who use aluminum rods to create automotive parts are classified as a user of commodities.

We identify producers of commodities in the data using the Bureau of Economic Analysis Make and Use tables. We identify 64 five-digit NAICS codes corresponding to raw material commodities in the Make and Use tables. A firm is classified as a producer of commodities if it is both treated and belongs to a producer NAICS industry. All non-producer treated firms are classified as users.

Summary Statistics

Table 2 defines the variables used in the paper.

INSERT TABLE 2 ABOUT HERE

Table 3 presents the summary statistics for both the treated and the control sample.

INSERT TABLE 3 ABOUT HERE

There are a total of 1,228 treated firms and 3,038 control firms. Treated firms appear to be statistically different than control firms along some observable dimensions, however, this is not unexpected given that these firms operate in different industries. We note that our main analyses are designed to account for any such heterogeneity, so that time-invariant level differences in firm characteristics do not compromise the identification assumptions. Also, while some of the variables are statistically different, the differences do not generally appear to be *economically* different from each other. For instance, the average market capitalization of treated firms is \$3.97 billion, while it is \$2.95 billion for the control group.

Identification Strategy

The economic mechanism outlined in Section 1 predicts that an increase in passive investing decreases the informational quality of commodity futures prices (e.g. a decrease in the financial efficiency). As a result, firms that condition their production decisions upon futures prices experience degradations in real outcomes. The econometric challenge, however, lies in cleanly identifying this effect because passive investing, financial efficiency, and firm decisions are co-determined in general equilibrium. For example, while passive investing may affect firm production decisions through financial efficiency, investors may change their passive investing strategies because of real economic fundamentals. Thus, an identification problem naturally arises in a simple OLS regression setting and valid statistical inference becomes impossible without a source of exogenous variation.

We attempt to identify the real effects of passive investing by exploiting the financialization of the commodity futures market as a source of exogenous variation in passive investing. As discussed in the Introduction, financialization resulted in a significant increase in the amount of uninformed investment in commodity futures.[14] Moreover, theory suggests financialization only affects firms who rely on commodity prices as inputs to their production decisions. The setting naturally lends itself to a difference-in-differences (DD) analysis. For a sample firm i in year t, the DD regression equation is:

$$y_{i,t} = \alpha + \beta D(i,t) + \delta_i + \delta_t + \varepsilon_{i,t}, \tag{18}$$

The variable $y_{i,t}$ is a real outcome variable of interest. The variable $D(i,t)$ is an indicator variable that is equal to 1 if firm i is treated and $t \geq 2004$, and zero otherwise. A firm i is treated if it is commodity sensitive, as defined in Section 2. The variables δ_i and δ_t are firm and year fixed-effects, respectively. The fixed-effects specification ensures that identification cannot be compromised by either firm-specific time-invariant omitted variables or time-varying firm-invariant omitted variables and avoids the problems associated with endogenous control variables (Gormley and Matsa (2014)). In untabulated results we repeat the analysis without the inclusion of controls and the coefficient estimates of β are statistically indistinguishable from the analysis with controls. This adds support to the idea that treatment is truly exogenous (Roberts and Whited (2012)).

[14] For example, financialization lowered the institutional impediments (e.g. participation costs) of investing in commodity futures via the introduction of commodity index funds. This established a new "bridge" through which previously orthogonal financial shocks, such as investor diversification needs, could propagate into commodity futures prices.

The key identification assumption needed for β to identify the causal effect of passive investing on firm outcomes is that the parallel trends assumption holds. That is, in the absence of treatment, the average change in the treatment group would have been equal to the average change in the control group. There are two main ways in which the parallel trends assumption may be violated in our setting. First, if the observed sharp increase in trading activity was endogenous (e.g. due either to a favorable or unfavorable signal about future demand) and completely unrelated to financialization, then we may mechanically recover a significant treatment effect. This explanation seems unlikely in our setting. Irwin and Sanders (2011) show that the jump in trading during financialization comes almost entirely from passive, index-based investment. Moreover, in Section 3 we show that our effects are present only in the set of firms sensitive to index commodities.

Second, the existence of any correlated time-varying within-firm omitted variables may compromise the identification assumption. We attempt to mitigate this concern by adding specifications that include control variables and running several falsification tests. Specifically, in Section 4 of the paper we show that our results are robust to both placebo treatment groups and placebo treatment dates. In addition, if the control variables are correlated with any time-varying within-firm omitted variables, the treatment coefficient would change when we include/exclude the control variables. The fact that control variables do not materially affect the coefficient estimates helps alleviate this identification concern.

3. Does Index Trading in Commodity Markets impact Firms?

This section tests the impact of passive investing on the real economy. We examine the impact of commodity market financialization on heavily commodity-exposed firms. We then explore whether the financialization of commodity markets exerts a heterogeneous impact on firms which *use* commodities, relative to firms which *produce* commodities. In addition, we test several theoretical predictions about the relation between commodity prices and the economic activity of firms. The results suggest that passive investing in financial markets can negatively impact the real economy.

A number of empirical papers document significant changes in commodity market trading in the mid-2000s. Between 2003 and 2008, the dollar value of commodity index-related instruments grew from $15 billion to more than $200 billion (Tang and Xiong (2012), CFTC (2008)). While there is not a single, precise, date on which this event occurred, the extant literature pins 2004 as the beginning of the financialization of commodity markets (Basak and Pavlova, 2015; Tang and Xiong, 2012; Boons, Roon, and Szymanowska, 2014; Domanski and Heath, 2007).[15] As a consequence of this sharp increase in passive investing, the dynamics of commodity prices changed. Henderson, Pearson, and Wang (2015) show that uninformed flows into commodity-linked notes, in particular, lead to significant changes in commodity prices. In other words, the results suggest uninformed investing leads to more noise in commodity futures prices.

Tang and Xiong (2012) examine the change in trading behavior resulting from financialization and suggest that the structural change is driven by the accessibility of index commodities. Irwin and Sanders (2011) document an increase in open interest at the beginning of 2004 after a decade of stability. In fact, the data shows a dramatic pattern: between 2003 and 2009, commodity index investment by institutional investors increased from $15 billion to $250

[15] Christoffersen and Pan (2014) discuss this point in greater detail and note that, “Most authors including Baker (2012), Baker and Routledge (2012), Hamilton and Wu (2013), and Ready (2014) date financialization to take effect sometime in the 2004-2005 period.”

billion. Irwin and Sanders (2011) also report that over the same time period, commodity index trade increases from roughly 10% of open interest, to 30-40% of open interest.

Difference-in-Difference Estimation: Volatility

To formally test the impact of the financialization of commodity markets, we examine real economic measures of firm performance. As discussed in Section 1, the theoretical model in Sockin and Xiong (2015) suggests a feedback effect between commodity futures prices and firm performance. If firms extract signals from commodity futures prices, then we expect firm performance to decline as future prices become less stable. The model in Sockin and Xiong (2015) generates three relevant testable predications:

(i) The volatility of total costs increases post-financialization for commodity sensitive firms.

(ii) The volatility of profits increases post-financialization for commodity sensitive firms.

(iii) The volatility of stock returns increases post-financialization for commodity sensitive firms.

We test these predictions using annual difference-in-difference regressions of the form:

$$y_{i,t} = \alpha + \beta D(i,t) + \delta_i + \delta_t + \varepsilon_{i,t}, \tag{18}$$

where y_{its} is one of four possible measures of firm financials, either the: (i) volatility of stock returns, (ii) the volatility of Return on Assets before Extraordinary Items, (iii) the volatility of Cost of Goods Sold / Assets, or (iv) the volatility of Cash Flow / Assets, for firm i on date t with treatment status s. As previously discussed, in equation (18) the variable $D(i,t)$ is an indicator variable that is equal to 1 if firm i is treated and $t \geq 2004$, and zero otherwise. To control for possible unobserved heterogeneity at the firm level and for possible systematic variation in economic conditions, we include firm and year fixed effects in even number models.[16] The results are shown in Table 4, with *t*-statistics, calculated using standard errors clustered by firm and year, presented below the coefficient estimates in italics.

INSERT TABLE 4 ABOUT HERE

Interestingly, the coefficient on the interaction term (hereafter, the treatment effect) is positive and statistically significant in all models; the results suggest the financialization of commodities is associated with increased volatility for commodity sensitive firms. This is true across all four measures of firm performance: Stock Returns, Return on Assets (ROA), Cost of Goods Sold (COGS), and Cash Flow. Specifically, the treatment effect is 0.006 in model (2) for *Volatility of Stock Returns* and the result is statistically significant at the 10% level or higher. Moreover, the results are economically large; the Treatment Mean (reported in Table 3) for the *Volatility of Stock Returns* is 0.03, thus financialization implies a 20% increase in stock return volatility for treated firms. Similarly, the effect is economically large for *ROA*, *COGS,* and *Cash Flow*. For *ROA*, financialization implies a 25% increase for treated firms while for *Cash Flow*, financialization implies a 7.5% increase for treated firms. While the effect is smallest for *COGS*, treatment firms still experiences a 6.7% increase in volatility following the financialization of commodity markets. Overall, the results confirm the main predictions derived in Section 1; increased passive investing in commodity markets is associated with increased volatility in total

[16] In the reported tables we double cluster standard errors by date and firm. However, due to the short nature of the time series, there are relatively few date clusters. In untabulated robustness tests we repeat the analysis clustering only by firm. We also repeat the analysis by collapsing the time dimension and doing the analysis in before-after changes. Both results have the same economic takeaway and are statistically stronger than those reported. To be conservative, we report the dual clustered standard errors which are higher than the alternate methods.

costs, profits, and stock returns for commodity sensitive firms. In other words, passive investing leads to real economic impacts.

Difference-in-Difference Estimation: Level of Accounting Variables

The results in the previous section show that passive investing in commodity markets led to increased volatility in a variety of firm financial measures. While the theoretical predictions discussed in Section 1 applied to the volatility of firm financial measures, it is economically important to know if passive investing also impacts the *level* of firm financial measures. Accordingly, we explore the relation between financialization and the level of firm financial variables. To investigate this, we again estimate a difference-in-difference regression like the model shown in equation (18), only this time the dependent variables are in levels: either the level of (1) Return on Assets before Extraordinary Items, (2) Cost of Goods Sold / Assets, (3) Cash Flow / Assets, or (4) Raw Inventory / Assets. In all models, standard errors are clustered by firm and year. The results are shown in Table 5.

INSERT TABLE 5 ABOUT HERE

As in Table 4, the coefficient on the interaction term represents the treatment effect. In all models the treatment effect suggests a decrease in firm performance. Following financialization, commodity sensitive firms experience a decrease in *Return on Assets*, an increase in *COGS*, decreases in *Cash Flow*, and increases in *Raw Inventory*. As before, the results are economically large. The Treatment Mean (reported in Table 3) for *ROA* is -0.02, thus the treatment effect of -0.022 implies that financialization is associated with almost a doubling in the negative *ROA* of treated firms. Post-financialization, commodity sensitive firms experience a significant decrease in their profitability. Similarly, the effect is economically large for *COGS* and *Raw Inventory*. For *COGS*, financialization implies a 4.4% increase for treated firms while for *Raw Inventory*, financialization implies a 10% increase for treated firms. Thus, passive investing is associated with higher inventories and worse cost of goods sold for commodity sensitive firms. Finally, while the coefficient on *Cash Flow* is negative, as expected, we note that it is not statistically significant and the effect is economically modest. The estimated treatment effect implies a 1.3% decrease in *Cash Flow* for treatment firms following financialization. Overall, the results in Table 4 and Table 5 suggest that commodity sensitive firms were harmed by the increased passive investing in commodities that occurred as a result of financialization.

Difference-in-Difference Estimation: Cost of Capital

Given the results in Table 4 and Table 5, we also test if passive investing in financial markets impacts the riskiness of commodity sensitive firms by examining their cost of capital. Others note that financialization has led to increased correlations between different commodities and between commodities and equities (e.g., Tang and Xiong (2012), Christoffersen and Pan (2014), Boons, de Roon, and Szymanowska (2014)). Our results so far document a relation between commodity prices and firm stock returns. These results, suggest financialization may impact a firm's beta, and more generally, its cost of capital.[17] Accordingly, we examine three measures of the cost of capital. The first measure is the traditional CAPM β. The second and third measures, *r(PEG)* and *r(DIV)*, are the suggested equity cost-of-capital proxies in Botosan,

[17] A firm's beta, by definition, is the covariance of its returns with the market scaled by the variance of the market. Given these results, we argue it is natural to examine whether the covariance between a firm's returns and the market has increased.

Plumee, and Wen (2011). The *r(PEG)* measure calculates the implied cost of capital from analyst earnings-per-share forecasts while the *r(DIV)* measure calculates the implied cost of capital from analyst target prices and dividends.

As shown in Table 6, all three measures point to the same conclusion: increased passive investing in commodity markets led to increased systematic risk in commodity sensitive firms.

INSERT TABLE 6 ABOUT HERE

Relative to control firms, commodity sensitive firms' CAPM β's increased by nearly 20 percent from the unconditional mean. In other words, post-financialization there is a higher degree of comovement between commodity sensitive firms and the equity market and thus, commodity sensitive firms exhibit more systematic risk. Moreover, the implied cost of equity capital increased by nearly 10 percent from the unconditional mean for both the *r(PEG)* and *r(DIV)* measures. In sum, passive investing in commodity markets led to increased systematic risk and increased capital costs for commodity sensitive firms.

Producer vs. User of Commodities

We have shown that commodity trading impacts commodity sensitive firms. So far, our definition of commodity sensitive firms includes both commodity producers (e.g., mining firms) and commodity users (e.g., manufacturing firms). As previously discussed, the model in Sockin and Xiong (2015) operates via an information channel: commodity users receive information about the future strength of the global economy from commodity futures prices. Thus, we'd expect financialization to impact commodity users, but not commodity producers. In this section, we present evidence consistent with this: the impact of financialization is concentrated in the users of commodities, but not in the producers.

We take two approaches. The first approach is to repeat the difference-in-difference analysis in equation (18), but separately define either (i) *Users* or (ii) *Producers* as treatment firms. In other words, we split commodity sensitive firms into sub-groups based on whether they produce or use commodities and independently test for impacts from passive investing for these subsamples. The second approach is to perform a triple difference-in-difference analysis, where the methodology takes equation (18) and adds another difference term based on whether a firm is a commodity *Producer* (1) or not (0). Therefore, a negative coefficient on the triple difference is positive when the effect is smaller for *Producers*. Table 7 contains the results from both approaches. As before, we examine the volatility of four variables: *Stock Returns*, *Return on Assets (ROA)*, *Cost of Goods Sold (COGS)*, and *Cash Flow*.

INSERT TABLE 7 ABOUT HERE

Columns 1, 3, 5, and 7 reports the coefficient of interest from the difference-in-difference regressions estimated separately for *Users* and *Producers*.[18] Columns 2, 4, 6, and 8 reports the coefficients for the triple difference approach. Consistent with theory, the results generally suggest commodity *Users* experience a larger increase in volatility than commodity *Producers*. The main exception is for the *Volatility of Stock Returns*, reported in column 1. While both the *User* and *Producer* coefficients are positive and statistically significant, the *Producer* coefficient of 0.008 is larger than the *User* coefficient of 0.005. However, in the Triple Difference

[18] We estimate *User Treat Effect* and *Producer Treat Effect* in separate regressions, but present them in the same column for brevity.

specification in column 2, the negative coefficient suggests that *Producers* experience a decline in stock return volatility relative to other firms. Focusing on the odd columns, the remaining three measures all show *Users* being more affected than *Producers*, with increased volatility in *ROA*, *COGS*, and *Cash Flow*. The *Triple Difference* results all point to the same conclusion, although the *ROA* coefficient is not statistically significant.

Thus, in sum, the *ROA*, *COGS*, and *Cash Flow* results all show that commodity *Users* experience larger effects than commodity *Producers*, consistent with feedback models like Sockin and Xiong (2015). While the results are somewhat mixed for stock return volatility, it is possible that stock returns are determined by investors views and not exclusively firm managers' decisions. If investors also misinterpret signals from the commodity futures market, we might expect stock returns to be impacted for all commodity sensitive stocks, not just *Users*.

As before, we also examine the level of firm performance. The results are shown in Table 8, with the same structure as Table 7.

INSERT TABLE 8 ABOUT HERE

Columns 1, 3, 5, and 7 reports the coefficient of interest from the difference-in-difference regressions ran separately for *Users* and *Producers*. Columns 2, 4, 6, and 8 reports the coefficients for the triple difference approach. All the results show *Users* underperforming, regardless of the variable analyzed or the methodology employed. *Users* experience a lower *ROA* than *Producers*. *Users* have a higher *COGS* than *Producers*. *Cash Flow* is unchanged for *Users* but increases for *Producers*. *Raw Inventory* increases more for *Users* than *Producers*, suggesting that *Users* have more inventory on-hand which ties up capital and suggests an inefficiency in the supply chain. Moreover, the triple difference analysis leads to the same conclusions. The only caveat being that the COGS coefficient just misses the tenth percentile statistical significance cutoff.

Overall, the results in Section 3 show that, following the financialization of commodity markets, commodity sensitive firms experience increased volatility in their stock returns, cost of goods sold, cash flows, and profits. Moreover, these firms experience increases in the level of their cost of goods sold and cost of capital and experienced decreases in their cash flows and return on assets. In other words, passive investing in commodity markets hurts firms which use commodities. Nonetheless, while our results do show that passive investing impacts the real economy, we are careful to avoid making welfare statements about our findings. In Section 4, below, we discuss the economic interpretation of our results in greater detail. We also discuss our identifying assumptions and several robustness checks.

4. Economic Channel, Identification, and Robustness

Economic Channel

The preceding section shows that increased passive investing in commodity futures markets led to worse firm performance. However, as noted by Bray (1981), futures prices can impact production in multiple ways. First, prices can impact firm budget constraints, and in that capacity, they directly impact firm operations. Second, futures prices can also lead to feedback effects whereby market participants learn about future economic conditions by observing market prices today. Here we explore the channel through which passive investing impacts firm outcomes. To do this, we directly control for the level of each firm's cost of goods sold through time to account for the budget constraint channel. If passive investing impacts firms through the information channel, then we expect to find statistically significant results even after controlling for the budget constraints channel.

As before, we estimate a difference-in-difference regression as shown in equation (18), only we add the level of COGS as a control variable. The dependent variable is either: (i) the volatility of stock returns, (ii) the volatility of Return on Assets before Extraordinary Items, (iii) the volatility of Cost of Goods Sold / Assets, or (iv) the volatility of Cash Flow / Assets. The results are shown in Table 9.

INSERT TABLE 9 ABOUT HERE

In all models except the *Volatility of COGS*, we find that the treatment effect is still positive and statistically significant at the usual levels. The results suggest that passive investing in commodity markets leads to increased volatility in firm performance even after controlling for the direct (i.e.,. budget constraint) channel. In other words, the results suggest that passive investing leads to negative externalities in the real economy because it impedes the ability of agents to extract signals from market prices.

Identification

Although equation (18) eliminates the endogeneity concerns stemming from firm-specific time-invariant omitted variables, a remaining concern is that time-varying within-firm omitted variables are simultaneously driving outcomes. Viewed in terms of a counterfactual: would the changes in outcomes of commodity sensitive firms have been systematically different than those of control firms even if financialization did not occur? In a difference-in-differences framework, this concern is mitigated as long as the parallel trends assumption is met. That is, in the absence of treatment, the average change in the treatment group would have been similar to the average change in the control group (i.e., changes in control group outcomes serve as valid counterfactuals for treatment group outcomes).

Although the parallel trends assumption is inherently untestable, a variety of falsification tests are commonly performed as support. One such test is to repeat the difference-in-differences analysis using only the pre-event years. If the parallel trends assumption is true, then falsely assuming that treatment occurs in the years *before* it actually does (i.e., one, two, three, or four years before 2004) should yield null results. In unreported results we perform this test by re-estimating the baseline regression model for a restricted pre-event sample from 1998 to 2004. We find that when we falsely define treatment for the years 2000, 2001, and 2002, the estimated treatment effects are statistically indistinguishable from zero. However, for the year directly prior to treatment (2003), we find that some of the estimated treatment effects are statistically different from zero. This finding is not too concerning – as the initial influx of index investment and the effects of financialization may have started to appear near the end of 2003.

In other unreported results we re-estimate the baseline regression model using placebo treatment groups. If financialization only affected outcomes through its effect on commodity sensitive firms (e.g. an exclusion restriction), then the treatment effect should be statistically indistinguishable from zero for firms who should not be affected by financialization. We test this condition by randomly assigning treatment to firms and re-estimating equation (18) for one thousand placebo treatment groups. We find that the empirical distribution of the *t*-statistics for the treatment effects is indistinguishable from a t-distribution with the appropriate degrees of freedom. These results provide further support that the results are driven exclusively by the effect of financialization on commodity sensitive firms.

Robustness

Several empirical papers attribute financialization's impact on index commodities to a rise in passive index investment (Tang and Xiong (2012)). This conclusion is often supported by the observation that non-index commodities did not experience significant increases in volatility or correlations during this period. Therefore, in the Sockin and Xiong (2015) framework, the informational quality of non-index commodity prices should be relatively unchanged over the course of financialization. Furthermore, the production decisions of firms exposed to non-index commodities should be relatively unchanged if the predictions of Sockin and Xiong (2015) hold.

We test the validity of our results by examining the outcomes of firms who are sensitive to non-index commodities. If commodity sensitive firms are indeed affected by financialization via an information channel, then we should find no effect for firms that are sensitive to non-index commodities. Table 10 reports the results of the difference-in-differences analysis that assigns treatment to firms who are only sensitive to non-index commodities.

INSERT TABLE 10 ABOUT HERE

As expected, we find that the estimated treatment effects are statistically indistinguishable from zero for all but one outcome variable (*Returns* with a t-statistic of 1.85). In other words, firms who are exposed to the commodities that are not affected by financialization do not exhibit any noticeable change in the trajectory of their outcomes. These results provide further support that our main results are concentrated only in the expected group of firms.

Finally, one may wonder why commodity sensitive firms are affected by financialization if firms have the option to hedge their commodity exposures. There are several possible explanations. First, firms are limited in the extent they can hedge commodity price risks. The maximum tenure of most commodity derivatives is only two years. Therefore, firms must "roll" their hedging positions and ultimately bear the costs associated with long-term, structural shocks to commodity prices.[19] Second, in reality, firms are often reluctant to undertake large hedging positions. Guay and Kothari (2003) show that the amount of hedging done by most firms is economically small in relation to their entity-level risk exposures. For the 36 firms that use commodity derivatives in their sample, the median notional principal hedged is only $40 million.[20] Third, the informational effect of financialization on commodity prices cannot be hedged using derivatives. Sockin and Xiong's (2015) model implies that financialization reduces the informativeness of commodity prices about future demand. Thus, independent of any changes in the levels of prices, commodity sensitive firms must condition their production decisions on a noisier signal post-financialization.

Overall, our results are consistent with financialization affecting firms via the informational channel and not the cost channel. This is consistent with theoretical models of feedback effects from market prices to firms (e.g., Sockin and Xiong (2015), Goldstein and Guembel (2008)). Furthermore, our results supplement the empirical findings of Henderson,

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[19] Hershey's annual report provides anecdotal evidence on this phenomenon. They detail that "Although we use forward contracts and commodity futures and options contracts, where possible, to hedge commodity prices, commodity price increases ultimately result in corresponding increases in our raw material and energy costs. If we are unable to offset cost increases for major raw materials and energy, there could be a negative impact on our financial condition and results of operations."

[20] This includes commodity forwards, futures, swaps, and options. However, it does not include long-term purchase and sale contracts.

Pearson, and Wang (2015) that suggest that uninformed, passive investing affects prices and price efficiency. However, it is worth noting that we cannot make any inferences about whether financialization makes futures prices better or worse signals about future economic conditions. Indeed, the fact that financialization resulted in negative real effects for commodity sensitive firms is consistent with both an increase and a decrease in futures price efficiency. The Sockin and Xiong (2015) model predicts that decreases in futures price efficiency is associated with worse firm performance. On the other hand, a special case of the Goldstein and Yang (2014) model suggests that increases in price efficiency can be associated with worse firm performance as well.

5. Conclusion

Does passive investing in financial markets impact the real economy? Or, alternatively, is it merely a sideshow which transfers wealth and risk from one trader to another? In this paper, we explore these questions by examining the link between firms and passive investing in commodity futures markets. Our results provide novel evidence that passive investing leads to negative externalities in the real economy because it impedes the ability of agents to extract signals from market prices.

We start by examining the relation between firm financial measures and the financialization of commodity markets in 2004. Using a difference-in-difference analysis, we find that firms which use commodities experience increases in their cost of goods sold and cost of capital, decreases in their cash flows and return on assets, and increased volatility in their stock returns. In other words, commodity sensitive firms appears to be hurt by the increase in passive investing that occurred as a result of the financialization of commodity markets. We then examine the economic channel through which passive investing hurts firms. Theory suggests that futures prices can affect asset demand in at least two ways (Bray (1981)): futures prices can impact firm budget constraints or they can impact the information sets of agents. Our results suggest that passive investing in commodity markets hurts firms because it impedes the ability of agents to extract signals from market prices. In other words, passive investing is not merely a side-show which transfers wealth between agents: it impacts real economic outcomes.

While it might be tempting to conclude that passive investing decreases welfare because we show it negatively impacts the real economic performance of commodity sensitive firms, it is possible that passive investing leads to benefits too. While this issue is beyond the scope of our paper, we do note that some existing evidence supports this view. For example, Boons, de Roon, and Szymanowska (2014) show that the financialization of commodity markets led to increased diversification for investors. Overall, our results show passive investing leads to negative externalities on the real economy, however future research should continue to explore the overall welfare implications.

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Table 1. Commodity Futures Contracts by Exchange

The table lists commodities with futures contracts traded in the U.S. or U.K. The left panel lists commodities which are part of an index, while the right panel displays non-index commodities. We categorize commodities into three groups: *Energy*, *Agriculture*, and *Metals*. *Exchange* is the name of the exchange on which the commodity trades: CME is the Chicago Mercantile Exchange, ICE is Intercontinental Exchange, LME is the London Metals Exchange, and NYMEX is the New York Mercantile Exchange.

Index Commodities		**Non-Index Commodities**	
Commodity	**Exchange**	**Commodity**	**Exchange**
Energy		***Energy***	
Crude Oil (WTI + Brent)	NYMEX	Propane	CME
Heating Oil	NYMEX	Ethanol	CME
Gasoline (RBOB)	NYMEX		
Natural Gas	NYMEX		
Agriculture		***Agriculture***	
Corn	CME	Rice	CME
Soybeans	CME	Oats	CME
Wheat (Chicago and Kansas)	CME	Lumber	CME
Soybean Oil	CME	Orange Juice	ICE
Coffee	ICE		
Cotton	ICE		
Sugar	ICE		
Cocoa	ICE		
Cattle (Feeder and Live)	CME		
Lean Hogs	CME		
Metals		***Metals***	
Gold	NYMEX	Tin	LME
Silver	NYMEX	Molybdenum	LME
Copper	NYMEX	Platinum	NYMEX
Aluminium	LME	Palladium	NYMEX
Nickel	LME		
Zinc	LME		

Table 2. Variable Definitions

The table defines key variables used in the paper. The sample properties and construction are discussed in detail in Section 2 of the text.

Variable Name	Definition
σ(Returns)	Calculated from CRSP as the standard deviation of daily returns over the calendar year.
σ(ROA), σ(ROAIB), σ(COGS/Assets)	Calculated from COMPUSTAT using the standard deviation of quarterly ROA (ROAIB, COGS/Assets) for the year. Quarterly ROA (ROAIB, COGS/Assets) is calculated as niq/atq (ibq/atq, cogsq,atq).
σ(Cash Flow/Assets)	Calculated from COMPUSTAT using the standard deviation of quarterly cash flow divided by quarterly assets. Quarterly cash flow is defined as cfq = oiadpq – accrualsq, where accruals are given by: accrualsq = [actq(t) – actq(t-1)]-[cheq(t)-cheq(t-1)]-[lctq(t) – lctq(t-1))]+ [dlcq(t) – dlcq(t-1)] – dpq. Observations with missing quarterly asset values are dropped. Quarterly cash and cash equivalents (cheq) and debt in current liabilities (dlcq) are set equal to zero if missing.
ROA, ROAIB	Calculated from COMPUSTAT using annual ni/at and ib/at.
Cash Flow	Calculated from COMPUSTAT as cf = oiadp – accruals, where accruals is defined analogously to accrualsq in the σ(Cash Flow/Assets) definition.
σ(GSCI Returns)	Calculated from DATASTREAM as the standard deviation of daily total returns on the S&P GSCI over the calendar year.
σ(Market)	Calculated from the FAMA-FRENCH dataset as the standard deviation of total market returns, where mktret = mktrpm + rf.
CAPM β	Retrieved directly from the CRSP annual beta files.
r(PEG), r(DIV)	Measures of the expected cost of equity capital, E[$r(i, t) \mid t\text{-}1$], as defined in Botosan, Plumlee, and Wen (2011).
Post Indicator	An indicator variable equal to one if the observation year is greater than or equal to 2004.
Treated	An indicator variable equal to one if the firm is treated. A firm is treated if its average pre-2004 mentions of any in-index commodity group (as defined in Table 1) falls in the top decile of mentions for that in-index commodity group.

Table 3. Summary Statistics

The table shows summary statistics for the sample which contains 24,776 observations at the firm-year level for the time period 2000 to 2007. *Market Capitalization* and *Total Assets* are from CRSP and expressed in thousands of U.S. dollars, *σ(Equity Returns)* is the annual volatility of each stock's returns calculated as the standard deviation of daily returns from CRSP, *Return on Assets* is return on assets before extraordinary items from Compustat, *σ(ROA)* is the standard deviation of quarterly *Return on Assets*, *COGS / Assets* is the ratio of cost-of-goods sold to total assets from Compustat, *σ(COGS / Assets)* is the standard deviation of quarterly *COGS / Assets*, *Cash Flow / Assets* is the ratio of quarterly cash flow to assets from Compustat, σ(Cash Flow / Assets) is the standard deviation of quarterly *Cash Flow / Assets*, *Raw Inventory / Assets* is ratio of raw inventory to total assets from Compustat, *LN(Cash)* is the natural log of cash from Compustat, *Treatment Mean* is the mean value of each variable for treatment firms, *Control Mean* is the mean value of each variable for control firms, and *Treatment – Control* is the difference in means between treatment and control firms. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variable	Mean	Median	1st	99th	Standard Deviation	Treatment Mean	Control Mean	Treatment – Control
Market Capitalization	3,256.72	16,946.40	5.99	354.91	58,003.23	3,967.60	2,954.32	1,013.28
Total Assets	2,941.35	16,210.49	12.96	341.64	40,776.00	4,082.45	2,456.32	1,626.13***
σ(Equity Returns)	0.04	0.02	0.01	0.03	0.12	0.03	0.04	-0.01***
Return on Assets (ROA)	-0.06	0.32	-1.37	0.03	0.27	-0.02	-0.07	0.05***
σ(ROA)	0.03	0.08	0.00	0.01	0.34	0.02	0.03	-0.01***
COGS / Assets	0.76	0.72	0.01	0.57	3.52	0.75	0.77	-0.02
σ(COGS / Assets)	0.03	0.04	0.00	0.01	0.19	0.03	0.03	0.00
Cash Flow / Assets	0.06	0.22	-0.84	0.10	0.43	0.08	0.05	0.04***
σ(Cash Flow / Assets)	0.04	0.05	0.00	0.03	0.24	0.04	0.04	-0.00***
Raw Inventory / Assets	0.04	0.05	0.00	0.02	0.24	0.04	0.03	0.01***
LN(Cash)	20.53	81.90	0.00	1.86	375.06	24.63	18.79	5.84**

Table 4. Difference-in-Difference Regression: Volatility of Firm Financials

The table contains difference-in-difference results for panel regressions of the form:

$$y_{i,t,s} = \beta_0 + \beta_1 1_{[Treated]} + \beta_2 1_{[Treatment\ Period]} + \beta_3 1_{[Treated]} \times 1_{[Treatment\ Period]} + \varepsilon_{i,t,s}$$

where y_{its} is either the: volatility of stock returns, volatility of Return on Assets before Extraordinary Items, volatility of Cost of Goods Sold / Assets, or volatility of Cash Flow / Assets, for firm *i* on date *t* with treatment status *s*. $1_{[Treated]}$ is an indicator variable which equals one for treated firms and zero otherwise, $1_{[Treatment\ Period]}$ is an indicator variable which equals one during the treatment period (2004 to 2007) and zero otherwise, and *Treatment Effect* is the coefficient on ($1_{[Treated]} \times 1_{[Treatment\ Period]}$). We discuss the definition of treated firms and the treatment period in Section 2 of the text. Even models include firm and year fixed effects. *t*-statistics are presented below the coefficient estimates, in italics, and are calculated using standard errors clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable							
	Volatility of Stock Returns		**Volatility of Return on Assets**		**Volatility of COGS / Assets**		**Volatility of Cash Flow / Assets**	
Explanatory Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Treatment Effect	0.007***	0.006***	0.008***	0.005**	0.002*	0.002**	0.003***	0.003**
	(11.93)	*(5.33)*	*(4.38)*	*(2.55)*	*(1.90)*	*(2.50)*	*(2.66)*	*(2.25)*
$1_{[Treated]}$	-0.010***		-0.012***		0.000		-0.006***	
	(-13.44)		*(-6.97)*		*(0.10)*		*(-6.64)*	
$1_{[Treatment\ Period]}$	-0.022***		-0.016***		-0.006***		-0.007***	
	(-65.16)		*(-13.82)*		*(-10.22)*		*(-9.73)*	
Firm Fixed Effect	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Year Fixed Effect	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
N	24,640	24,134	24,724	24,227	24,586	24,084	22,873	22,873

Table 5. Difference-in-Difference Regression: Level of Firm Financials
The table contains difference-in-difference results for panel regressions of the form:

$$y_{i,t,s} = \beta_0 + \beta_1 1_{[Treated\,]} + \beta_2\, 1_{[Treatment\ Period]} + \beta_3\, 1_{[Treated\,]} \times 1_{[Treatment\ Period]} + \varepsilon_{i,t,s}$$

where y_{its} is either the level of: (1) Return on Assets before Extraordinary Items, (2) Cost of Goods Sold / Assets, (3) Cash Flow / Assets, or (4) Raw Inventory / Assets, for firm *i* on date *t* with treatment status *s*. $1_{[Treated\,]}$ is an indicator variable which equals one for treated firms and zero otherwise and $1_{[Treatment\ Period]}$ is an indicator variable which equals one during the treatment period (2004 to 2007) and zero otherwise. We discuss the definition of treated firms and the treatment period in Section 2 of the text. *t*-statistics are presented below the coefficient estimates, in italics, and are calculated using standard errors clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable							
Explanatory	**Return on Assets**		**COGS / Assets**		**Cash Flow / Assets**		**Raw Inventory / Assets**	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Treatment Effect	-0.046***	-0.022*	0.023	0.033***	-0.022***	-0.001	0.004**	0.004***
	(-5.62)	*(-1.88)*	*(1.38)*	*(2.61)*	*(-3.81)*	*(-0.19)*	*(2.57)*	*(3.17)*
$\mathbf{1_{[Treated]}}$	0.066***		-0.032		0.047***		0.008***	
	(8.08)		*(-1.36)*		*(7.61)*		*(3.61)*	
$\mathbf{1_{[Treatment\ Period]}}$	0.092***		-0.003		0.031***		-0.001	
	(17.13)		*(-0.26)*		*(8.15)*		*(-1.29)*	
Firm Fixed Effect	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Year Fixed Effect	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
N	24,769	24,271	24,766	24,268	16,447	16,060	24,206	23,721

Table 6. Difference-in-Difference Regression: Firm Cost of Capital

The table contains difference-in-difference results for panel regressions of the form:

$$y_{i,t,s} = \beta_0 + \beta_1 1_{[Treated]} + \beta_2\, 1_{[Treatment\ Period]} + \beta_3\, 1_{[Treated]} \times 1_{[Treatment\ Period]} + \varepsilon_{i,t,s}$$

where y_{its} is one of three possible cost of capital measures: *CAPM β, r(PEG)* measure, or the *r(DIV)* measure for firm *i* on date *t* with treatment status *s*. *CAPM β* is from CRSP and *r(PEG)* and *r(DIV)* are the expected cost of equity capital as in Botosan, Plumlee, and Wen (2011), $1_{[Treated]}$ is an indicator variable which equals one for treated firms and zero otherwise, $1_{[Treatment\ Period]}$ is an indicator variable which equals one during the treatment period (2004 to 2007) and zero otherwise, and *Treatment Effect* is the coefficient on ($1_{[Treated]} \times 1_{[Treatment\ Period]}$). We discuss the definition of treated firms and the treatment period in Section 2 of the text. Even models include firm and year fixed effects. *t*-statistics are presented below the coefficient estimates, in italics, and are calculated using standard errors clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Explanatory Variables	**Dependent Variable**					
	CAPM β		**r(PEG)**		**r(DIV)**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Treatment Effect	0.246***	0.225***	0.009**	0.013***	0.030*	0.061***
	(3.66)	*(11.16)*	*(2.43)*	*(3.28)*	*(1.74)*	*(4.86)*
$\mathbf{1_{[Treated]}}$		-0.103***		-0.012***		-0.070***
		(-6.08)		*(-3.77)*		*(-5.36)*
$\mathbf{1_{[Treatment\ Period]}}$		0.243***		-0.010***		-0.187***
		(23.78)		*(-5.70)*		*(-24.29)*
Firm Fixed Effect	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Year Fixed Effect	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
N	23,893	24,399	6,620	6,800	6,998	7,293

Table 7. Difference-in-Difference Regression: Volatility of Firm Financials for Commodity Producers versus Users

The table contains difference-in-difference results for panel regressions of the form:

$$y_{i,t,s} = \beta_0 + \beta_1 1_{[Treated]} + \beta_2 1_{[Treatment\ Period]} + \beta_3 1_{[Treated]} \times 1_{[Treatment\ Period]} + \varepsilon_{i,t,s}$$

where y_{its} is either the: volatility of stock returns, volatility of Return on Assets before Extraordinary Items, volatility of Cost of Goods Sold / Assets, or volatility of Cash Flow / Assets, for firm i on date t with treatment status s. $1_{[Treated]}$ is an indicator variable which equals one for treated firms and zero otherwise, $1_{[Treatment\ Period]}$ is an indicator variable which equals one during the treatment period (2004 to 2007) and zero otherwise, and *Treatment Effect* is the coefficient on ($1_{[Treated]} \times 1_{[Treatment\ Period]}$). We discuss the definition of treated firms and the treatment period in Section 2 of the text. † denotes that odd numbered models contain results from two separate regressions (i.e., we estimate *User Treat Effect* and *Producer Treat Effect* in separate regressions, but present them in the same column for brevity). *t*-statistics are presented below the coefficient estimates, in italics, and are calculated using standard errors clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable							
Explanatory Variables	**Volatility of Stock Returns**		**Volatility of Return on Assets**		**Volatility of COGS / Assets**		**Volatility of Cash Flow / Assets**	
	(1)†	**(2)**	**(3)†**	**(4)**	**(5)†**	**(6)**	**(7)†**	**(8)**
User Treat Effect	0.005***		0.006**		0.006**		0.003**	
	(4.96)		*(2.78)*		*(2.73)*		*(2.92)*	
Producer Treat Effect	0.008***		0.002		0.001		-0.001	
	(5.33)		*(0.48)*		*(0.28)*		*(-0.40)*	
Triple-Difference		-0.005*		-0.012		-0.019**		-0.010***
		(-1.80)		*(-1.26)*		*(-2.17)*		*(-5.57)*
Diff-in-Diff		0.006***		0.006***		0.006***		0.003***
		(5.09)		*(2.76)*		*(2.74)*		*(3.04)*
Producer-Post		0.009***		0.009		0.016*		0.007***
		(3.09)		*(0.99)*		*(1.84)*		*(3.48)*
Firm Fixed Effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year Fixed Effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	24,134	24,134	24,226	24,226	24,227	24,227	24,084	24,084

Table 8. Difference-in-Difference Regression: Level of Firm Financials for Commodity Producers vs. Users

The table contains difference-in-difference results for panel regressions of the form:

$$y_{i,t,s} = \beta_0 + \beta_1 1_{[Treated]} + \beta_2 1_{[Treatment\ Period]} + \beta_3 1_{[Treated]} \times 1_{[Treatment\ Period]} + \varepsilon_{i,t,s}$$

where y_{its} is either the level of: (1) Return on Assets before Extraordinary Items, (2) Cost of Goods Sold / Assets, (3) Cash Flow / Assets, or (4) Raw Inventory / Assets, for firm i on date t with treatment status s. $1_{[Treated]}$ is an indicator variable which equals one for treated firms and zero otherwise and $1_{[Treatment\ Period]}$ is an indicator variable which equals one during the treatment period (2004 to 2007) and zero otherwise. We discuss the definition of treated firms and the treatment period in Section 2 of the text. † denotes that odd numbered models contain results from two separate regressions (i.e., we estimate *User Treat Effect* and *Producer Treat Effect* in separate regressions, but present them in the same column for brevity). *t*-statistics are presented below the coefficient estimates, in italics, and are calculated using standard errors clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable							
Explanatory	**Return on Assets**		**COGS / Assets**		**Cash Flow / Assets**		**Raw Inventory / Assets**	
Variables	**(1)**†	**(2)**	**(3)**†	**(4)**	**(5)**†	**(6)**	**(7)**†	**(8)**
User Treat Effect	-0.027***		0.027**		-0.010		0.007***	
	(-2.59)		*(2.00)*		*(-1.41)*		*(3.48)*	
Producer Treat Effect	0.016		0.042		0.037***		0.006*	
	(1.23)		*(1.45)*		*(3.32)*		*(1.68)*	
Triple-Difference		0.079**		-0.078		0.062***		-0.031***
		(1.97)		*(-1.60)*		*(2.67)*		*(-3.04)*
Diff-in-Diff		-0.027**		0.031**		-0.008		0.008***
		(-2.40)		*(2.28)*		*(-1.08)*		*(3.91)*
Producer-Post		-0.044		0.098**		-0.019		0.032***
		(-1.08)		*(2.23)*		*(-1.06)*		*(3.17)*
Firm Fixed Effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year Fixed Effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	24,271	24,271	24,268	24,268	23,721	23,721	24,080	24,080

Table 9. Difference-in-Difference Regression: Volatility of Firm Financials Controlling for the Budget Constraint Channel

The table contains difference-in-difference results for panel regressions of the form:

$$y_{i,t,s} = \beta_0 + \beta_1 1_{[Treatment\ Effect\ ]} + \beta_2\ FE_i + \beta_3\ FE_t + \beta_4\ COGS_{i,t,s} + \varepsilon_{i,t,s}$$

where y_{its} is either the: volatility of stock returns, volatility of Return on Assets before Extraordinary Items, volatility of Cost of Goods Sold / Assets, or volatility of Cash Flow / Assets, for firm *i* on date *t* with treatment status *s*. $1_{[Treatment\ Effect\ ]}$ is an indicator variable which equals one for treated firms during the treatment period and zero otherwise, FE_i is a firm fixed effect, FE_t is a time fixed effect, and $COGS_{i,t,s}$ is the level of cost of goods sold for firm *i* in period *t*. We discuss the definition of treated firms and the treatment period in Section 2 of the text. *t*-statistics are presented below the coefficient estimates, in italics, and are calculated using standard errors clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: Volatility of			
Explanatory	**Returns**	**ROA**	**COGS**	**Cash Flow**
Variables	**(1)**	**(2)**	**(3)**	**(4)**
Treatment Effect	0.006***	0.004**	0.001	0.003**
	(5.245)	(2.191)	(1.269)	(1.964)
COGS/Assets	0.002***	0.024***	0.029***	0.013***
	(3.045)	(5.737)	(15.972)	(7.042)
Firm Fixed Effect	*Yes*	*Yes*	*Yes*	*Yes*
Year Fixed Effect	*Yes*	*Yes*	*Yes*	*Yes*
N	24,126	24,221	24,078	22,380

Table 10. Difference-in-Difference Regression: Firm Financials and Non-Index Commodities
The table contains difference-in-difference results for panel regressions of the form:

$$y_{i,t,s} = \beta_0 + \beta_1 1_{[Treated\,]} + \beta_2\, 1_{[Treatment\ Period]} + \beta_3\, 1_{[Treated\,]} \times 1_{[Treatment\ Period]} + \varepsilon_{i,t,s}$$

where y_{its} is either the: volatility of stock returns, volatility of Return on Assets before Extraordinary Items, volatility of Cost of Goods Sold / Assets, volatility of Cash Flow / Assets, Return on Assets before Extraordinary Items, Cost of Goods Sold / Assets, Cash Flow / Assets, or Raw Inventory / Assets for firm *i* on date *t* with treatment status *s*. $1_{[Treated\,]}$ is an indicator variable which equals one for treated firms and zero otherwise, $1_{[Treatment\ Period]}$ is an indicator variable which equals one during the treatment period (2004 to 2007) and zero otherwise, and *Treatment Effect* is the coefficient on $(1_{[Treated\,]} \times 1_{[Treatment\ Period]})$. We discuss the definition of treated firms and the treatment period in Section 2 of the text. Even models include firm and year fixed effects. *t*-statistics are presented below the coefficient estimates, in italics, and are calculated using standard errors clustered by firm and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable							
	Volatility of				Level of			
Explanatory Variables	**Returns**	**ROA**	**COGS / Assets**	**Cash Flow / Assets**	**ROA**	**COGS / Assets**	**Cash Flow / Assets**	**Inventory / Assets**
Treatment Effect	0.002*	0.003	0.001	0.003	-0.006	-0.003	0.003	0.004
	(1.85)	*(0.65)*	*(0.69)*	*(0.96)*	*(-0.37)*	*(-0.16)*	*(0.28)*	*(1.25)*
Firm Fixed Effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year Fixed Effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	21,975	22,078	21,974	20,470	22,113	22,110	21,614	21,941