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ROBO-REGULATOR: ALGORITHMIC DETECTION OF MARKET MANIPULATION

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Robo-Regulator: Algorithmic Detection of Market Manipulation

*Reid B. Stevens and Jeffery Y. Zhang**

April 25, 2017

Abstract

In recent years, a tremendous increase of trading activity in physical commodity markets has created concern among policymakers and regulators over the price impact of speculation and manipulation. The former is a regular market activity, where rational market agents act in anticipation of a future shock. The latter is irregular, and involves market agents hoarding assets in order to artificially raise their prices. Detecting manipulation is not a costless enterprise. The objective of this article is to facilitate that task by providing regulators with an algorithm—a robo-regulator—that acts as a fire alarm for detecting manipulative schemes. This algorithm uses a novel approach that exploits a commodity's production complement in order to test whether the commodity is affected by manipulation. We apply the algorithm to three recent, well-publicized U.S. Senate investigations of commodity price spikes in order to test whether any episode was caused by manipulation. The algorithm shows that the crude oil price increase in the early-2000s was not caused by manipulative schemes, but the wheat futures price spike in the mid-2000s and the aluminum regional price spike in the early-2010s were caused by manipulation.

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I. Introduction

Objective

The task of keeping markets healthy and functioning properly is a costly one, and regulators have limited resources.[1] Moreover, markets are becoming more complex, not less. Regulatory agencies must therefore constantly conduct constrained optimization. They have limited staff and resources and cannot request their lawyers to perform a thorough investigation into every instance of alleged fraud or manipulation. This begs the question, what is the best method for regulators to screen allegations? How do they pick which follow-up interviews to conduct?

The objective of this article is to facilitate the constrained optimization of regulators by providing them with an algorithm to detect market manipulation in real time. Lawyers and economists in regulatory agencies can use the algorithm described in the following sections as a "robo-regulator." One can think of this detection algorithm as an analogue to the "robo-advisors" in the investment world.[2] However, the goal of this algorithm is not to replace human regulators but to assist with the surveillance and enforcement process.

The topic of market manipulation was recently thrust back into the spotlight by the revelation of Goldman Sachs's scheme in the United States regional aluminum market.[3] Between 2010 and 2014, the regional price of aluminum in the United States increased threefold. Using a novel approach that exploits aluminum's production complement, Stevens and Zhang (2016)[4]

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[1] *See, e.g.*, Matt Robinson & Benjamin Bain, *Wall Street Cops Reined In as SEC Braces for Trump Budget Cuts* (Mar. 6, 2017), Bloomberg, *available at* https://www.bloomberg.com/news/articles/2017-03-06/wall-street-cops-reined-in-as-sec-braces-for-trump-budget-cuts; Corey Boles & Jamila Trindle, *CFTC Budget Request Is Cut*, Wall Street Journal (Nov. 14, 2011), *available at* https://www.wsj.com/articles/SB10001424052970203503204577038653502512684; Ben Protess, *Regulators Decry Proposed Cuts in C.F.T.C. Budget* (Feb. 24, 2011), New York Times, *available at* https://dealbook.nytimes.com/2011/02/24/regulators-decry-proposed-c-f-t-c-budget-cuts.

[2] *See, e.g.*, Tom Baker & Benedict G. C. Dellart, *Regulating Robo Advice Across the Financial Services Industry* (Mar. 2017), UPenn, Inst. L. & Econ. Res. Paper No. 17-11, *available at* https://ssrn.com/abstract=2932189; Melanie L. Fein, *Robo-Advisors: A Closer Look* (Jun. 2015), *available at* https://ssrn.com/abstract=2658701.

[3] After investigating the alleged aluminum manipulative scheme, the U.S. Senate included the following recommendation for financial regulators: "The Office of Financial Research should study and produce recommendations on the broader issue of how to *detect, prevent, and take enforcement action* against all entities that use physical commodities or related businesses to manipulate commodity prices in the physical and financial markets." U.S. Senate, Permanent Subcommittee on Investigations, *Wall Street Bank Involvement with Physical Commodities*, Majority and Minority Staff Report (2014), at 12 (emphasis added).

[4] *See* Reid B. Stevens & Jeffery Y. Zhang, *Slipping through the Cracks: Detecting Manipulation in Regional Commodity Markets* (December 21, 2016), *available at* https://ssrn.com/abstract=2888992.

demonstrate that the increase was *artificially caused* by Goldman's accumulation of an unprecedented level of aluminum inventories in their Detroit warehouses.[5] Notably, the authors also show that the aluminum scheme had significant real effects on downstream industrial producers and consumers. Manipulation in other markets, if left undetected and undeterred, would be similarly detrimental. It is therefore in society's best interest that financial regulators implement effective real-time surveillance to detect and stop such behavior.

Stevens and Zhang (2016) construct an econometric algorithm for real-time detection of manipulation.[6] When applied to the U.S. aluminum market, the algorithm is able to detect the Goldman scheme in late 2011, which is more than six months before news outlets publicized the scheme. That version of the algorithm is well suited to monitor metals traded on the London Metal Exchange like aluminum and copper. This article builds upon the Stevens and Zhang (2016) algorithm so that it can detect manipulation in the physical commodity market as a whole, including energy commodities (oil and natural gas) and agricultural commodities (wheat, corn, and soy).

In addition to facilitating the surveillance and enforcement operations of regulators, this article provides the research community with a conceptually simple, yet empirically rigorous method to distinguish harmful manipulation from regular speculation. In the process of researching alleged episodes of manipulation—for example, in the case of the recent U.S. aluminum regional price increase—researchers regularly heard the following counterargument: "Yes, we see that aluminum inventories went up and then aluminum prices went up. But how can you prove this was not caused by a benign market actor who merely believed aluminum prices would be higher tomorrow and so decided to store more today?" This simple hypothetical typically ends such inquiries into manipulation in the academic community.

This article presents a robust response to that hypothetical, one that can distinguish manipulation (actions by market participants that *artificially cause* an asset price to increase) from speculation (actions taken by market participants *in anticipation* of an asset price increase). For an illustration of the theory underlying the response, consider the fact that aluminum and copper are production complements. That is, aluminum is commonly alloyed with copper in the industrial production process, rather than being used in its pure form. The implication is that a demand shock affecting aluminum would also affect copper. In the case of the Goldman aluminum scheme, aluminum inventories skyrocketed.

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[5] At the peak of the scheme, warehouses owned by Goldman Sachs in Detroit held over half of the total U.S. aluminum stock.

[6] The algorithm is inspired by the multivariate trend break tests developed by Jushan Bai, Robin L. Lumsdaine & James H. Stock, *Testing For and Dating Common Breaks in Multivariate Time Series*, The Review of Economic Studies, Vol. 65, 395-432 (1998).

If this sudden increase were caused by benign speculators anticipating an aluminum demand shock, then rational market actors would also expect copper to receive a positive demand shock in the future. And if that were true, we should see copper inventories increase in the present. Yet the data clearly show that copper inventories were unaffected, and copper prices were stable. Market actors did not expect a positive demand shock to aluminum, nor did one materialize. Of course, this analysis of demand shocks rests upon the premise that there were no supply shocks that disrupted either commodity. This assumption is checked by the algorithm.

Specific Commodities

This article expands the algorithm's coverage into energy commodities like oil and natural gas, and agricultural commodities like wheat, corn, and soy. These commodities have been the target of previous allegations of market manipulation.

In 2006, the U.S. Senate Permanent Subcommittee on Investigations produced a staff report titled, "The Role of Market Speculation in Rising Oil and Gas Prices: A Need to Put the Cop Back on the Beat."[7] The report begins by noting the significant price increase in crude oil from 2000 to 2006, and then states "traditional forces of supply and demand cannot fully account for these increases."[8] The report focuses on financial institutions like hedge funds, which have poured billions of dollars into energy commodities. The claim is that the speculation by these institutions artificially drove up the price of crude oil.[9]

[7] U.S. Senate, Permanent Subcommittee on Investigations, *The Role of Market Speculation in Rising Oil and Gas Prices: A Need to Put the Cop Back on the Beat*, Staff Report (2006).

[8] *Id.* at 1.

[9] *See id.* at 2 ("The large purchases of crude oil futures contracts by speculators have, in effect, created an additional demand for oil, driving up the price of oil to be delivered in the future in the same manner that additional demand for the immediate delivery of a physical barrel of oil drives up the price on the spot market. As far as the market is concerned, the demand for a barrel of oil that results from the purchase of a futures contract by a speculator is just as real as the demand for a barrel that results from the purchase of a futures contract by a refiner or other user of petroleum.").

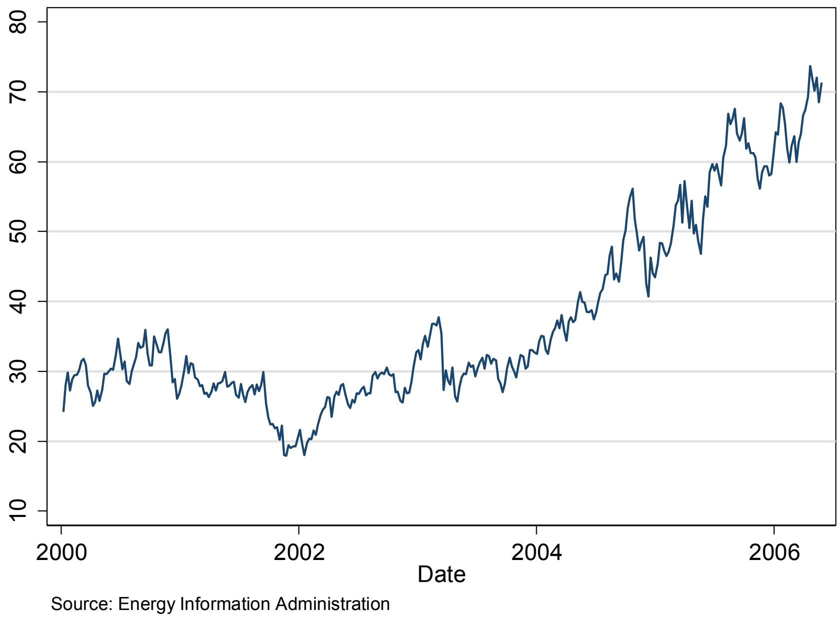


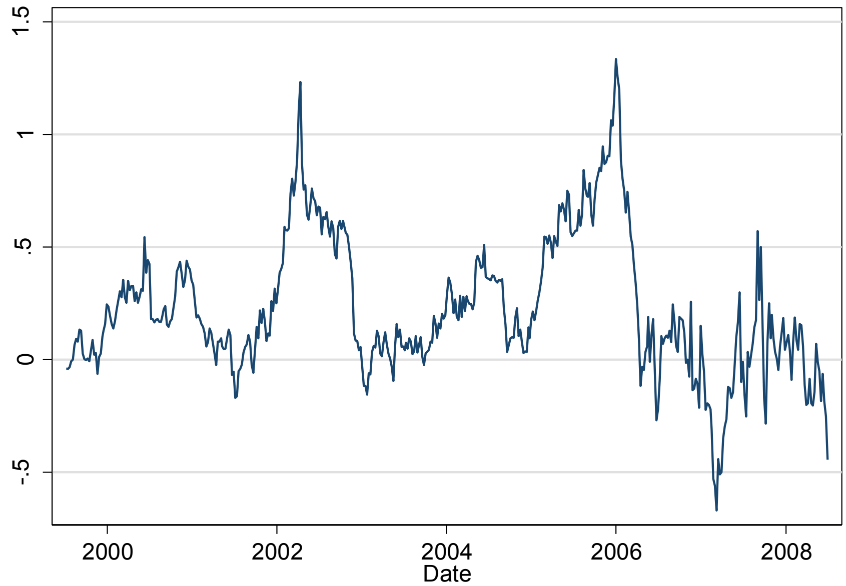
Figure 1: Rising Price of Crude Oil[10]

In 2009, the U.S. Senate Permanent Subcommittee on Investigations looked into speculation in the wheat market.[11] Similarly, the report begins by documenting a massive increase in the price of wheat. The report then pivots to the influx of capital into the market from institutional investors like hedge funds and pension funds, and presents analysis to conclude that speculation did contribute to the increase in prices.[12]

[10] Here, the price of crude oil is the spot price.

[11] U.S. Senate, Permanent Subcommittee on Investigations, *Excessive Speculation in the Wheat Market*, Majority and Minority Staff Report (2009).

[12] *See id.* at 9 ("The investigation found that, in 2008, the greater demand for Chicago wheat futures contracts generated by index traders was a significant factor in the relative increase in the wheat futures price compared to the cash price (the basis) during that period. In addition, a significant cause of the resulting price disparity between the futures and cash markets, which was far greater than the normal gap between futures and cash prices, was the purchases of Chicago wheat futures by index traders.").



Source: Chicago Mercantile Exchange

Figure 2: Wheat Basis[13]

In 2014, the U.S. Senate Permanent Subcommittee on Investigations turned its attention to aluminum.[14] The resulting report follows the formula by first pointing out an abnormal increase in the regional price of aluminum. But then, instead of focusing on speculation, the report unearths a Goldman Sachs scheme to manipulate aluminum inventories.[15]

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[13] Here, the basis is defined as the spot price minus the one-month futures price.

[14] U.S. Senate, Permanent Subcommittee on Investigations, *Wall Street Bank Involvement with Physical Commodities*, Majority and Minority Staff Report (2014).

[15] *See id.* at 169–70 (summarizing the Goldman Sachs scheme).

Figure 3: Rising Regional Price[16] of Aluminum

In each of the above three investigations, regulators and policymakers saw a significant price increase in a commodity and asked, "What is going on here? What's causing the price spike?" There are two possibilities: either the commodity was affected by speculation or by manipulation.[17] Speculation is a normal market activity,[18] albeit not an activity liked by the general public. A market agent places bets based on expectations of future demand for the commodity. Speculation is crucial for market operations because companies oftentimes need to hedge risk; in order to hedge risk, a company needs to find a counterparty who is willing to take the opposite side of the bet. Manipulation, on the other hand, involves undertaking a set of artificial actions in order to affect prices. For example, an agent who hoards an asset in order to distort regular trading of that asset is manipulating the market for that asset. The goal of the algorithm presented in this article is to distinguish between speculation and manipulation. In doing so, the algorithm can confirm, modify, or rebut, the conclusions in those three Senate reports.

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[16] Here, the regional price of aluminum is the Midwest Premium.

[17] Recall that the algorithm rules out supply shocks, so we are left with these two explanations.

[18] "According to the CFTC, a speculator does not produce or use the commodity, but risks his or her own capital trading futures in that commodity in hopes of making a profit on price changes." U.S. Senate, *supra* note 7, at 2.

Preview of Results

Using the algorithm, which is described in detail in the next section, regulators cannot rule out that the crude oil price increase during the early-2000s was due to benign speculation or natural shifts in global supply and demand. The algorithm provides no evidence suggesting the price spike was due to manipulation. The algorithm does find, however, that the wheat price spike observed by the 2009 Senate Report was caused neither by benign market speculation nor by a supply shock. The wheat price increase was likely caused by manipulative practices, which means regulators should have pursued further investigations. Finally, the algorithm demonstrates that the regional aluminum price increase observed by the 2014 Senate Report was indeed caused a manipulative scheme. This is not to say that the Senate Report's account of the Goldman Sachs scheme is 100 percent accurate; but it is very likely that manipulation—and not speculation—caused the astronomical rise in regional aluminum prices.

The rest of the article is organized as follows: Section II describes the three-step algorithm in detail, starting with a thorough explanation of why having a complement is necessary. Section III applies the algorithm to the alleged cases of manipulation and speculation highlighted above. The analysis is very detailed, so the reader can clearly see the inner workings of the algorithm. Section IV concludes.

II. Algorithm

The purpose of this section is to present an algorithm that is simple yet rigorous. The version presented here contains three "steps," which are described in detail below. The data requirements are also minimal—the regulator only needs to provide a "price" series and an "inventory" series for each commodity. The price series can be based on a commodity's spot price, futures price, basis, or regional price. If the regulator is not constrained by data availability, the regulator could test each one separately for completeness. Similarly, the inventory series can be based on commodity inventories traded on financial exchanges—like the London Metal Exchange (LME) or the Chicago Mercantile Exchange (CME)—and, if available, stocks held by producers. The regulator should first assess the availability of the data and then decide which to use; of course, the regulator can test each series separately for completeness. The logic applies in each case.

Using these simple ingredients as inputs, the algorithm flags any abnormal scenarios that are potentially caused by manipulation rather than by speculation. Regulators should therefore use this algorithm as a "fire alarm." If the alarm goes off, regulators should consider taking additional investigative measures.

Step 1: Obtain Complements

The first step of the algorithm is to find a commodity (or a basket of commodities) that is a "complement" to the commodity under investigation. In order to qualify as a complement, the two commodities must react similarly if affected by a demand shock. In other words, if the demand for commodity x increases, then the demand for the complement of commodity x should also increase. In the ideal world, the demand shock will affect the two in an identical manner (in sign and magnitude). In the real world, however, regulators might have to live with spillover effects, namely, a one-unit demand increase to commodity x might only result in a half-unit demand increase to its complement.

Regulators have multiple resources at their disposable to locate complements. First, they can analyze de-trended annualized returns of commodities to see how strongly they correlate before the alleged episode of manipulation or speculation. Second, they can look at elasticities provided by industry sources, academic studies, or government institutions like the United States Department of Agriculture. Third, regulators can use an econometric "demand model" like the one provided in Appendix A. Of course, none of these three methods are dispositive; but if all available sources point in the same direction, then one can be more confident that the result is robust.

Finding a complement is crucial because regulators can employ it in a proof-by-cases method in order to distinguish between manipulation and speculation. To see the logic, consider the following hypothetical, propositions, and proofs.

HYPOTHETICAL: Suppose that regulators witness a sudden, sustained, significant increase in both the price of c_1 relative to c_2 and the inventories of c_1 relative to c_2.[19] If that occurs, then there are two possible explanations to walk through: (1) The phenomenon was caused by speculation, that is, some market actors believe a positive demand shock will hit c_1 in the near future and so they store now in the present. Their goal is to sell c_1 at a higher price in the future. (2) The phenomenon was caused by manipulation, that is, some market actors are not reacting to an anticipated demand shock, but rather manipulating physical inventories in order to artificially increase the price.

PROPOSITION 1: Because c_1 and c_2 are complements, explanation (1) is not possible. That is, if regulators see a sudden, sustained, significant increase in the price of c_1 relative to c_2 and also in the inventories of c_1 relative to c_2, then regulators know the underlying cause was not due to benign market actors reacting to expected demand shocks.

PROOF OF PROPOSITION 1: Assume, for the purpose of contradiction, that market actors are reacting in response to an anticipated demand shock to c_1 in the future. If this is true, then it must also be true that the anticipated demand shock will affect c_2 in the future. This is because, by definition of "complement" in this context, a demand shock that increases the consumption and price of c_1 will also increase the consumption and price of c_2. The implication is that rational market actors should also store more of c_2 in the present, with the goal of selling it at a higher price in the future, when the demand shock hits c_1. And if this were true, then inventories of c_2 should also have dramatically increased in the present. Yet this is what not regulators witnessed. Thus, it cannot be true that the sudden, sustained, significant price and inventory differences between c_1 and c_2 were due to benign reactions by rational market actors.

Note that explanation (2) survives. That is, if regulators witness significant price and inventory differences between c_1 and c_2, they can be sure that something suspicious is happening in the market and should investigate accordingly.

PROPOSITION 2: Regulators cannot use substitutes to make the same logical deductions. Under both manipulation and speculation, substitutes yield the same price and inventory outcomes.

PROOF OF PROPOSITION 2: To see why, consider substitute commodities s_1 and s_2. Here, assume that a demand shock that boosts the consumption and price

[19] Here, we are not referring to a minor price or inventory difference between c_1 and c_2. In the case studies below, one sees tremendous differences—multiples, in fact. If the differences were not substantial, Congress would not have investigated.

of s_1 will reduce the consumption and price of s_2. Can regulators rule out explanation (1)? No.

Suppose rational market actors expect a demand shock to s_1 in the near future. As a result, they should store more of s_1 in the present, in hopes of selling s_1 at a higher price in the future. If they store more of s_1 in the present, however, this means more of s_2 will be consumed in the present because the two are substitutes. This will lead to an increase in inventories of s_1 and a decrease in inventories of s_2.

Importantly, the manipulative case yields similar outcomes with respect to price and inventory series, which makes the two explanations indistinguishable. Suppose a devious market actor hoards s_1 with a plan to artificially increase prices. Because s_1 and s_2 are substitutes, the market will simply use more of s_2 in the present. This results in an increase in inventories of s_1 and a decrease in inventories of s_2. This is the same outcome as the benign case.

Thus, regulators cannot use substitutes to distinguish between manipulation and speculation. The reason is because the same inventory and price outcomes occur in both cases. Regulators can, however, use complements to distinguish between manipulation and speculation because there should be no sustained, significant differences between the prices and inventories of complements.

It is important to note that, while regulators cannot use substitutes to the same theoretical effect in this algorithm, regulators can rest assured that manipulating substitutes will not be a frequent phenomenon. If a market actor were to manipulate a commodity, that actor would be wise to choose a commodity with complements and with no substitutes. If such a substitute did exist, industrial producers could simply substitute away from the manipulated commodity. In other words, the manipulator would not be able to corner the market, and would be left with a significant loss.

Step 2: Test For Trend Breaks

Assuming regulators have identified a complement, or a set of complements, they have to acquire the "price" and "inventory" data for the complement. Again, the price series can be based on a commodity's spot price, futures price, basis, or regional price. If the regulator is not constrained by data availability, the regulator could test each one separately for completeness. Similarly, the inventory series can be based on tradable inventories on an international exchange like the London Metal Exchange, or based on stocks held by producers. The regulator should first assess the availability of the data and then decide which to use; of course, the regulator can test each series separately for completeness. The logic described in Step 1 applies to all these scenarios.

Suppose the regulator has price series for complements c_1 and c_2—call them p_1 and p_2, respectively—and inventories for c_1 and c_2—call them i_1 and i_2, respectively. The goal is to check for sustained, significant deviations between p_1 and p_2, and also between i_1 and i_2. The easiest way to go about this, without losing empirical validity, is to analyze the difference between the series. That is, test for statistically significant "trend breaks" in both the $p_1 - p_2$ series and also in the $i_1 - i_2$ series using the multivariate test designed by Bai, Lumsdaine, and Stock (1998).[20] The precise test is described in Appendix B. The regulator should be suspicious if the algorithm shows trend breaks in both the price and inventory series. Such a trend break tells the regulator that the usual price and inventory patterns between two complementary commodities are breaking apart, when they should be moving in sync as described in Step 1.

It is important to note that the algorithm only moves forward to the next step if it detects a structural trend break that is *very* robust. Specifically, the break must be statistically significant at the 1 percent level and not dependent on particular start dates or end dates. This ensures that regulators are solidly in the hypothetical described in the first step, that is, there is actually a real empirical phenomenon worthy of being investigated further. Put another way: the regulators must see dense smoke, not just a small campfire.

Step 3: Rule Out Supply Shocks

In the theoretical discussions of Step 1, it is assumed that a benign market actor only reacts to demand shocks. Of course, a negative supply shock to a commodity could also drive up the price of that commodity. This in third step, the algorithm guards against the impact of sudden supply shocks such as weather shocks that affect agricultural output (e.g., a drought) or employment shocks that affect mining output (e.g., a strike by mine workers).

The precise details can be found in Appendix C. Conceptually, the algorithm takes as inputs the past history of production output of the commodities in question. Using past history of output, the algorithm estimates the production output that should exist in the period of question. We then compare the model's predicted production to actual production. A large difference between predicted and actual production indicates an unanticipated production shock.

By ruling out potential supply shocks, regulators who use this algorithm can analyze the trend breaks in Step 2 through the demand-speculation and manipulation lens of Step 1.

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[20] Jushan Bai, Robin L. Lumsdaine & James H. Stock, *Testing For and Dating Common Breaks in Multivariate Time Series*, Review of Economic Studies, Vol. 65, 395-432 (1998).

III. Application

Having laid out the framework of the algorithm in the previous section, we now proceed to test three recent, well-publicized investigations of commodity price spikes. Seeing the algorithm's steps in full will give the reader a clearer picture of its strengths and limitations.

Case 1: Oil

Recall that, in 2006, the U.S. Senate Permanent Subcommittee on Investigations looked into the significant price increase in crude oil prices from 2000 to 2006. See Figure 4 below. The resulting report argues that the price increases could not be accounted for by normal supply and demand. The report focuses mainly on the role of financial institutions like hedge funds, which have poured billions of dollars into energy commodities. In this case study, we apply the algorithm to help us answer the following: Was the surge in crude oil prices caused by manipulation? As a preview of the results, the algorithm shows that manipulation likely did not occur. Crude oil prices probably increased during that period because of speculation or natural market forces.

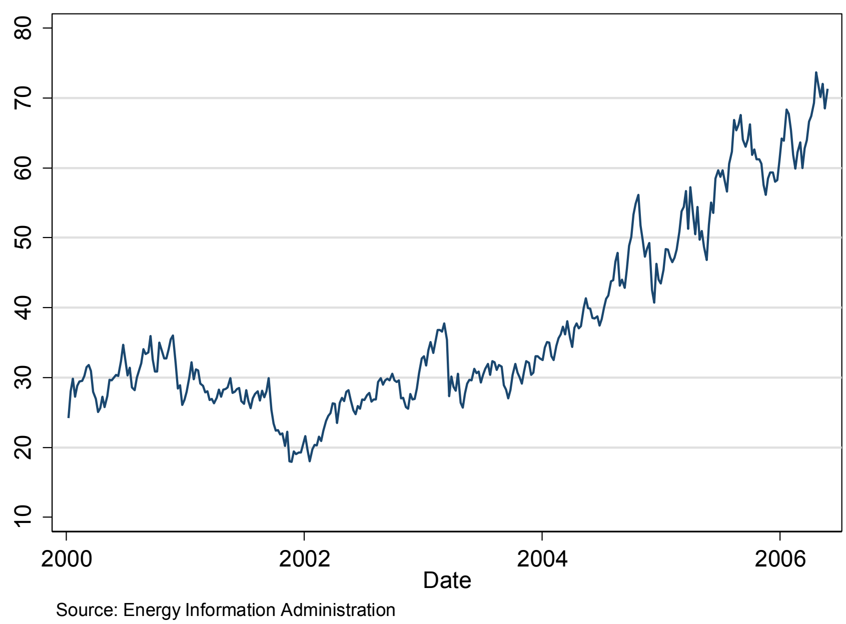

Figure 4: Rising Price of Crude Oil

<u>STEP 1:</u> In the first step, we search for a complementary commodity to oil. We want a commodity that reacts to demand shocks in the same way as oil. The answer is natural gas. The de-trended annualized returns of oil and natural gas are

highly correlated. See Figure 5 below. In addition, academic studies published in peer-reviewed journals find that oil and natural gas are indeed complements.[21] Finally, our own demand model shows that they two are complements.[22] Taken together, one can be fairly confident that the two are complements in the sense that they are both similarly affected by a demand shock.

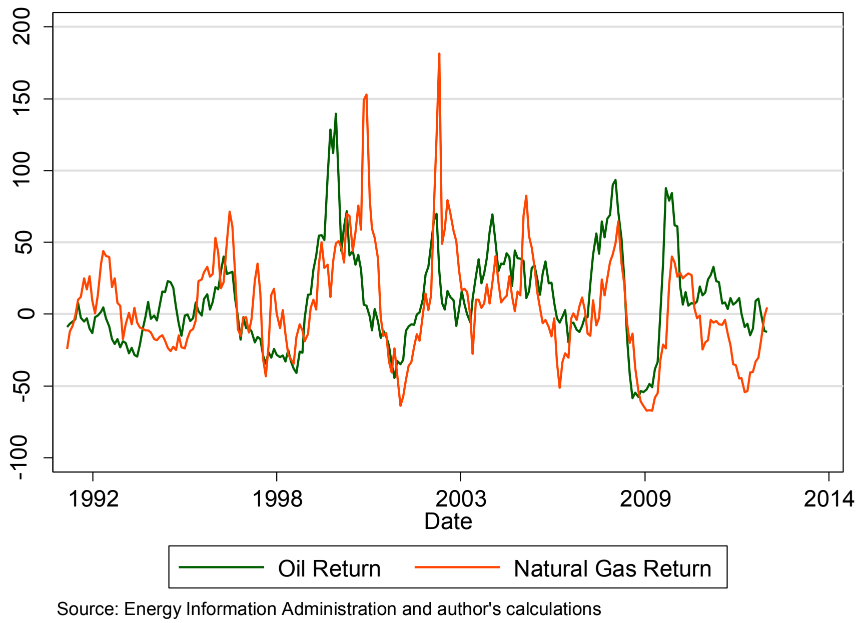

Figure 5: Detrended Annualized Returns of Oil and Natural Gas

STEP 2: Next, the algorithm searches for a multivariate trend break using the price difference between oil and natural gas, and using the inventory difference between oil and natural gas. For prices, the algorithm utilizes both spot and futures prices.[23] For inventories, the algorithm uses U.S. crude oil stock data, which do not include crude oil stocks in other countries and also do not include government crude oil stocks such as those in the U.S. strategic petroleum reserve.

Using the spot price of oil, the algorithm detects a highly significant trend break in 2005, which is within the time window studied by the U.S. Senate report. See Figure 6 below. However, the algorithm stops here and does not (need to) proceed to Step 3 because the trend break does not occur in both the price series and the inventory series.

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[21] *See, e.g.*, Christopher S. Rowland, James W. Mjelde & Senarath Dharmasena, *Policy Implications of Considering Pre-Commitments in US Aggregate Energy Demand System*, 102 Energy Policy 406 (2017).

[22] *See* Appendix A.

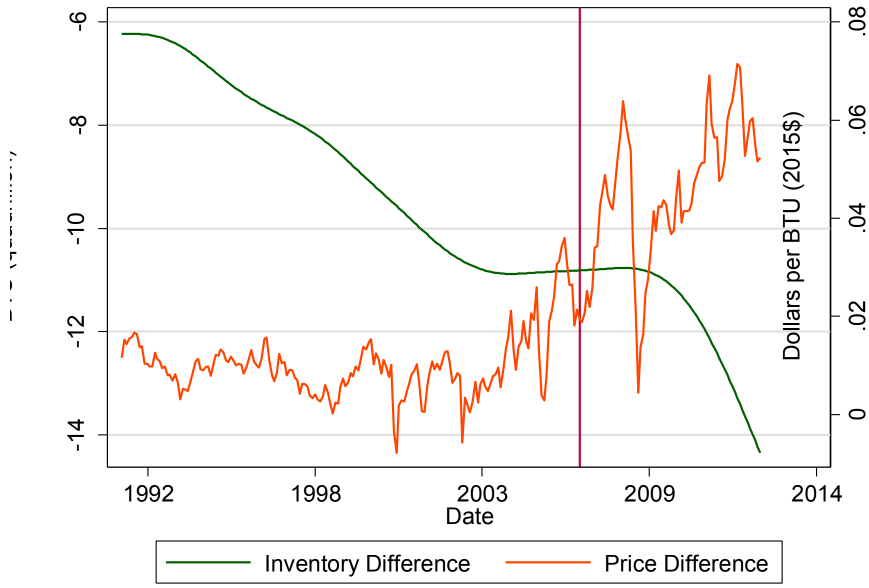
[23] Note that there is no regional price for crude oil.

Recall that the algorithm's baseline assumption is that regulators witness a sudden, sustained, significant increase in both the price of c_1 relative to c_2 and the inventories of c_1 relative to c_2. There has to be "breaks" in both the price and inventory series. If both series break, then there are two possibilities for the algorithm to analyze: (1) The phenomenon was caused by speculation, that is, some market actors believe a positive demand shock will hit c_1 in the near future and so they store now in the present. Their goal is to sell c_1 at a higher price in the future. (2) The phenomenon was caused by manipulation, that is, some market actors are not reacting to an anticipated demand shock, but rather manipulating physical inventories in order to artificially increase the price.

Looking at Figure 6, however, one can clearly see that the trend break detected by our algorithm is caused only by the divergent spot price series. The inventory series between oil and natural gas remained constant leading up to 2005 and even afterward. A manipulative scheme of the sort described in the previous section is based upon the accumulation of a sizeable inventory position, one that is sufficiently large to affect trades and delivery. Here, there is no increase whatsoever in crude oil inventory relative to that of natural gas.

Therefore, based on Step 1 and 2, a regulator can be fairly certain that a manipulation of the type described in the previous section did not occur in the crude oil market during the early-2000s. The significant rise in crude oil prices were likely caused by speculation or natural supply and demand forces.[24]

[24] *Cf.* Lutz Kilian & Daniel P. Murphy, *The Role of Inventories and Speculative Trading in the Global Market for Crude Oil*, 29 Journal of Applied Econometrics 454 (2014) (arguing that the price increase was driven largely by global demand).



Source: Energy Information Administration and author's calculations

Figure 6: Multivariate Break Test Using Oil and Natural Gas

Case 2: Wheat

In 2009, the U.S. Senate Permanent Subcommittee on Investigations also looked into speculation in the wheat market.[25] The report begins by documenting a massive increase in the futures price of wheat relative to its spot price, see Figure 7 below, and then pivots to the influx of capital into the commodity markets from institutional investors like hedge funds and pension funds. It concludes that speculation did contribute to the increase in prices. We apply the algorithm again to help us answer the following question: Was the increase in wheat prices caused by manipulation? Our algorithm shows that the U.S. Senate investigation should have reached a stronger conclusion. The algorithm sails through Steps 1, 2, and 3, which means regulators should have performed a more thorough investigation into potential market manipulation.

[25] U.S. Senate, Permanent Subcommittee on Investigations, *Excessive Speculation in the Wheat Market*, Majority and Minority Staff Report (2009).

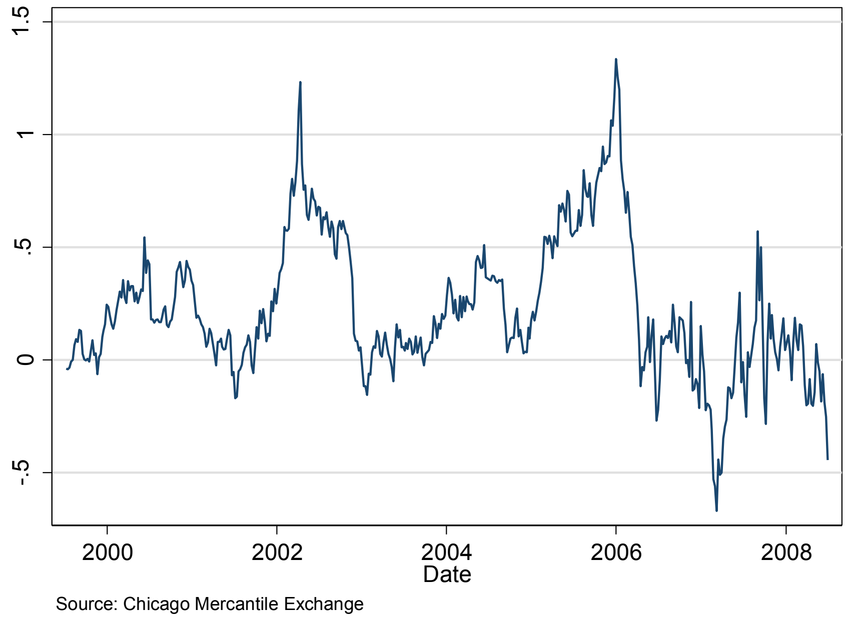


Figure 7: Wheat Basis

<u>Step 1:</u> In the first step, we search for a complement to wheat. Again, we want a commodity that reacts to demand shocks in the same way as wheat. Here, we have two commodities: corn and soy. The de-trended annualized returns of wheat, corn, and soy are strongly correlated. See Figure 8 below. In addition, government sources[26] and academic studies published in peer-reviewed journals[27] find that these commodities are indeed complements. Finally, our own demand model shows that they are complements.[28] Therefore, a regulator using this algorithm can be confident that these three commodities are complements in the sense that they are affected in the same way by a demand shock.

[26] *See* K. S. Huang & B. Lin, *Estimation of Food Demand and Nutrient Elasticities from Household Survey Data*, Food and Rural Economic Division, Economic Research Service, U.S. Department of Agriculture, Technical Bulletin Number 1887 (August 2000).

[27] *See* J. Bergtold, E. Akobundu & E. B. Peterson, *The FAST Method: Estimating Unconditional Demand Elasticities for Processed Foods in the Presence of Fixed Effects*, 29 *Journal of Agricultural and Resource Economics* 276 (2004).

[28] *See* Appendix A.

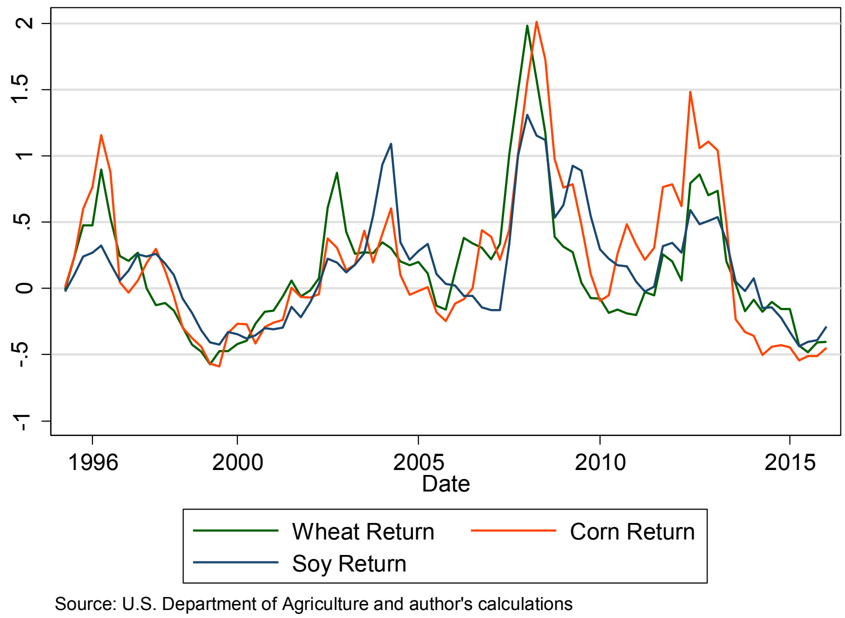


Figure 8: Detrended Annualized Returns of Wheat, Corn, and Soy

STEP 2: Next, the algorithm searches for a trend break using the price difference between the three series, and using the inventory difference between the three series. For prices, the algorithm tests the difference between spot and futures prices (the basis).[29] For inventories, the algorithm uses the U.S. Department of Agriculture's estimates of private wheat, corn, and soy inventories, which do not include inventories in other countries.

Using the basis of wheat, which was the specific focus of the 2009 U.S. Senate report, the algorithm detects a highly significant trend break in 2007, which is within the window period studied by the U.S. Senate report. See Figure 9 below. Notably, both the price series and the inventory series break—the price of wheat increases relative to the price of corn, and wheat inventories rise relative to corn inventories. But this double trend break should not occur given the premise that aluminum and copper are complementary commodities. See Proposition 1, *supra*. Thus, there is strong evidence that the wheat market was targeted by a manipulative scheme.

[29] Note that there is no regional price for wheat.

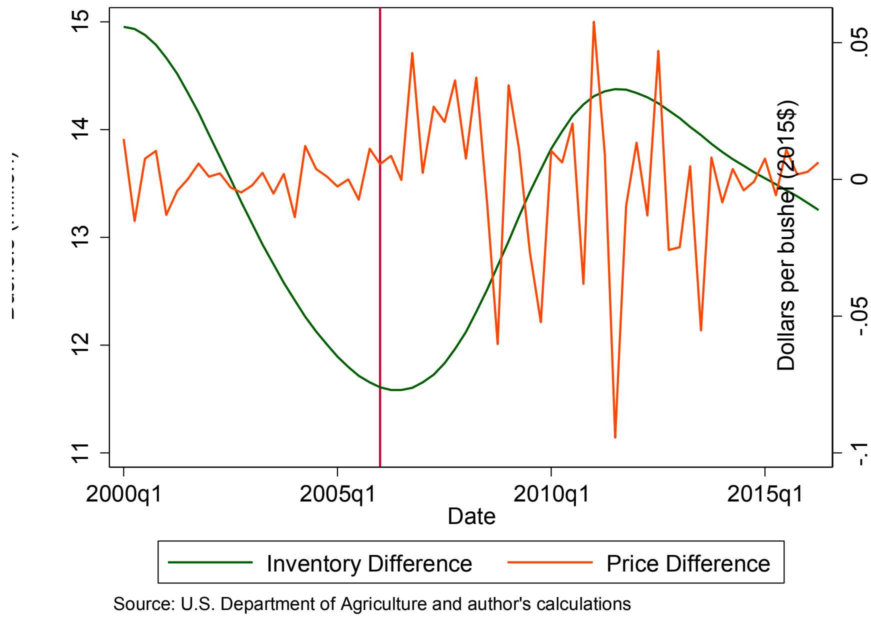


Figure 9: Multivariate Trend Break Test Using Wheat and Corn

STEP 3: In this last step, we ask whether the statistically significant break found in the previous step was possibly affected by a supply shock. The answer is no. See Figure 10 below. Using the VAR method outlined in the previous section, the algorithm finds no significant deviations in production levels during the time period under investigation.

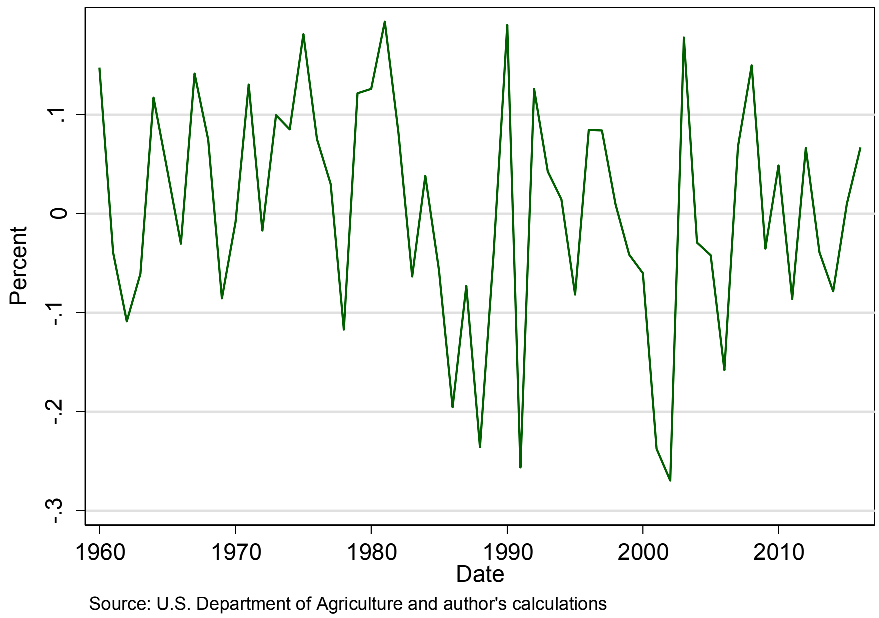


Figure 10: Wheat Production Shocks

Given Steps 1, 2, and 3 above, a regulator should conclude that the price increase pointed out by the 2009 Senate Report was caused neither by benign market speculation nor by a supply shock. It is likely that manipulation occurred in the wheat market. To be sure, this algorithm cannot tell regulators exactly how market actors manipulated the wheat market. But once the alarm goes off, regulators should pursue further investigations.

Case 3: Aluminum

In 2014, the U. S. Senate Permanent Subcommittee on Investigations turned its attention to aluminum.[30] The resulting report documents an unusual increase in the regional price of aluminum, see Figure 11 below, and then claims to uncover a Goldman Sachs scheme to manipulate aluminum inventories. Was the aluminum market manipulated? Most likely.

[30] U.S. Senate, Permanent Subcommittee on Investigations, *Wall Street Bank Involvement with Physical Commodities*, Majority and Minority Staff Report (2014).

Figure 11: Rising Regional Price of Aluminum

<u>STEP 1:</u> Once more, the first step is to search for a complement to aluminum, specifically a commodity that reacts to demand shocks in a similar fashion to aluminum. The answer is copper. The de-trended annualized returns of aluminum and copper are highly correlated. See Figure 12 below. In addition, industry sources explicitly state that these commodities are complements.[31] Finally, our own demand model shows that they are complements.[32] Taken together, a regulator using this algorithm can be sure that aluminum and copper are complements.

[31] *See* Aalco Metals Limited, *Aluminum Specifications, Properties, Classifications and Classes, Supplier Data* (2005).

[32] *See* Appendix A.

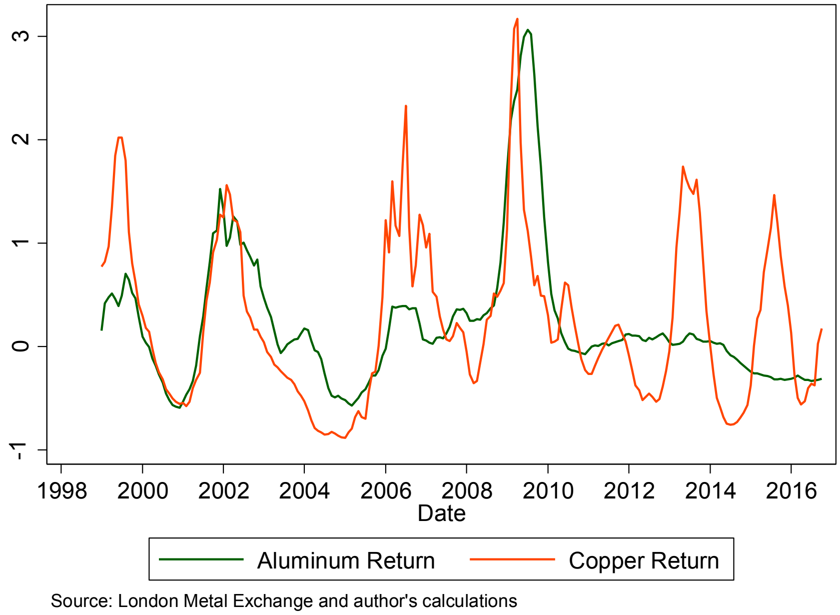


Figure 12: Detrended Annualized Returns of Aluminum and Copper

STEP 2: The algorithm searches for a multivariate trend break using the price difference between the aluminum and copper series, and using the inventory difference between the two series. For prices, the algorithm utilizes spot, futures, and regional (Midwest Premium) prices. For inventories, the algorithm uses U.S. inventory data based on traded aluminum on the London Metal Exchange.

Using the regional price of aluminum, which was the specific focus of the 2014 U.S. Senate report, the algorithm detects a highly significant trend break in 2012, which is within the window period studied by the U.S. Senate report. See Figure 13 below. It is important to note that both the inventory-difference series and the price-difference series increased. This means that aluminum inventories rose relative to copper inventories, and aluminum prices increased relative to copper prices. But this phenomenon—the two breaks—should not occur given the premise that aluminum and copper are complementary commodities. See Proposition 1, *supra*. Thus, there is strong evidence that the aluminum market was targeted by a manipulative scheme.

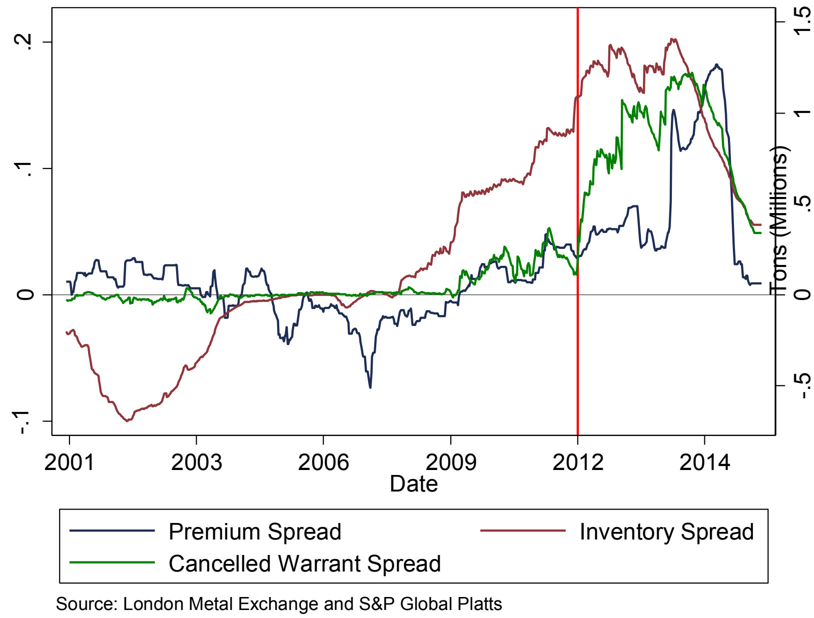


Figure 13: Multivariate Trend Break Using Aluminum and Copper

STEP 3: Finally, the algorithm checks whether the statistically significant break found in Step 2 was possibly affected by a supply shock. The answer is no. See Figure 14 below. Using the VAR method outlined in the previous section, the algorithm finds no significant deviations in production levels during the time period under investigation.

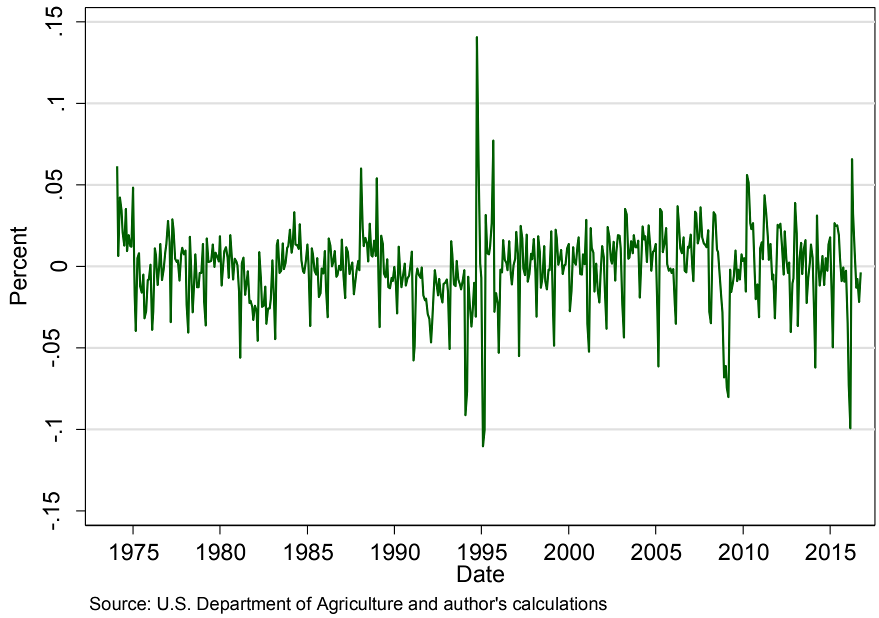


Figure 14: Aluminum Production Shocks

Therefore, one can conclude that the regional price increase noted by the 2014 Senate Report was probably caused a manipulative scheme. The algorithm does *not* tell us that the U.S. Senate Report's account of the Goldman Sachs scheme is 100 percent accurate. The algorithm only tells us that manipulation most likely occurred.

IV. Conclusion

In recent years, the tremendous increase in activity in physical commodity markets has created concern among policymakers over speculation and manipulation. The former is a subset of regular market activities. The latter is not. The objective of this article is to provide regulators with a tool—an algorithm to be specific—that can act as a "fire alarm" for manipulation. Once the regulator presses a button to active the algorithm, it will produce an output that either tells the regulator "nothing irregular here" or "please investigate further." Importantly, this detection algorithm should greatly enhance the efficacy of regulators given initial information opacity and budgetary constraints.

We apply this three-step algorithm to recent, well-known investigations of commodity price spikes—oil in 2006, wheat in 2009, and aluminum in 2014. In 2006, for instance, the Senate investigation concluded that market speculation was partly to blame for the increase in oil prices. Our algorithm shows that manipulation did not occur, but cannot differentiate between speculation and natural market forces. In 2009, the Senate investigation alleged that price of wheat was boosted by speculation. Our algorithm concludes that the investigations did not go far enough. It was most likely caused by manipulation, not benign speculation. In 2014, the Senate investigation got it right by observing that the U.S. aluminum market was manipulated. While our algorithm cannot prove or disprove a specific scheme, it can say that the price spike was caused by manipulation and not speculation.

Notably, this algorithm contains only three conceptually straightforward "steps." The data requirements are also minimal—the regulator needs to provide only a "price" series and an "inventory" series. The price series can be based on a commodity's spot price, futures price, basis, or regional price. If the regulator is not constrained by data availability, the regulator could test each one separately for completeness. Similarly, the inventory series can be based on tradable inventories on an international exchange like the London Metal Exchange, or based on stocks held by producers. The regulator should first assess the availability of the data and then decide which to use; of course, the regulator can test each series separately for completeness.

Finally, it is worth noting that the concept of using complements as a method for distinguishing manipulation from speculation can be extended more broadly, possibly into the realm of financial assets. For example, in the case of publicly traded stocks or bonds, one can certainly find "complements" in the sense that a pair of such assets would be affected similarly by a demand shock.

Appendix A

For each of the commodities within the energy, metal, and agricultural commodity groups, we determine whether those commodities are production complements or substitutes using estimates from Deaton and Muellbauer's (1980) almost ideal demand system (AIDS).[33] Following Serletis et al. (2010),[34] our AIDS model estimates the demand system for each commodity assuming a production function of the following form

$$Y_{commodity_i} = F(commodity_i, L, M, K, t)$$

where the gross output, $Y_{commodity_i}$, is modeled as a function of a specific commodity group and other inputs. We consider three specific commodity groups separately: the energy commodity group (oil and natural gas), the agricultural commodity group (wheat and corn), and the metals commodity group (aluminum and copper). The inputs in each demand model L, M, K are labor, material, and capital, respectively. The model also includes a technology index, *t*.

We assume the production function is weakly separable in each commodity. So, for example, the energy commodity input ($commodity_E$) can be written as $commodity_E = commodity_E(oil, natural\ gas)$, where $commodity_E(\cdot)$ is a homothetic aggregator function over the two energy types under consideration.[35] The agricultural commodity input and the metal commodity input can be similarly constructed.

Duality allows the production function to be rewritten as a cost function, assuming cost minimization subject to fixed production and technology levels,

$$C = C(P_E, P_L, P_M, P_K, t)$$

where C is the cost function, and P_i are the price aggregator functions for each of the factors. To estimate the elasticities, we need to find the demand function for each energy input. Shephard's lemma allows us to recover these demand functions from the price aggregator functions

[33] *See* Angus Deaton & John Muellbauer, *An Almost Ideal Demand System*, 70 American Economic Review 312 (1980).

[34] *See* Apostolos Serletis, Govinda R. Timilsina & Olexandr Vasetsky, *Interfuel Substitution in the United States*, 32 Energy Economics 737 (2010).

[35] *See* Apostolos Serletis, Govinda R. Timilsina & Olexandr Vasetsky, *Interfuel Substitution in the United States*, 32 Energy Economics 737 (2010).

$$S_{E_i} = \frac{\partial lnP_E}{\partial lnP_{E_i}}$$

These cost shares for individual commodities allow us to estimate own-price and cross-price elasticities. These cost shares can be written more explicitly as

$$w_i = \frac{p_i}{m} + \left(1 - \sum_i \frac{p_i}{m}\right)[\alpha_i + \sum_i \gamma_{ij} \ln(p_i) + \beta_i \ln\left(\frac{\sum_i p_i}{P}\right)] + \varepsilon_i$$

where w_i is the share of total expenditure for each energy source (oil and natural gas), p_i is the real price of energy, m is the total expenditures on energy, P is the Stone's price index $P = \sum_i w_i lnp_i$, and ε is the model residual. Since we use Stones' price index, as opposed to the translog price index, we estimate the Linear Approximation Almost Ideal Demand System.[36]

Estimation is complicated by the endogenity of m. The variable is endogenous because it is a product of the endogenous price and quantity variables. To address the endogeneity of m, we follow Capps et al. (1994) and instrument for m using predicted expenditures resulting from a regression of total expenditures on real gross domestic product and energy prices. This instrument replaces actual total expenditures by energy source, which are unobserved. With this instrument, we then estimate an iterated seemingly unrelated regression. The own-price and cross-price elasticities are presented for each commodity in Tables 1 through 3 below.

The cross-price elasticity for oil and natural gas is -0.45 (Table 1), which is about as large as the own-price elasticities for oil and natural gas, indicating the two goods are production complements. The cross-price elasticity for wheat and corn is -0.04 (Table 2), which is smaller than the own-price elasticity for wheat but close to the own-price elasticity for corn. Finally, the cross-price elasticity for aluminum and copper is -0.29 (Table 3), which is only somewhat smaller than the own-price elasticities. This confirms that copper and aluminum are production complements. Overall, the demand models confirm that the commodities analyzed in this paper are indeed production complements.

[36] *See* Christopher S. Rowland, James W. Mjelde & Senarath Dharmasena, *Policy Implications of Considering Pre-Commitments in US Aggregate Energy Demand System*, 102 Energy Policy 406 (2017).

	Oil	Natural Gas
Oil	-0.66	
Natural Gas	-0.45	-0.41

Table 1: Energy Commodity Demand Model Elastiticites

	Wheat	Corn
Wheat	-0.22	
Corn	-0.04	-0.05

Table 2: Agricultural Commodity Demand Model Elastiticites

	Aluminum	Copper
Aluminum	-0.33	
Copper	-0.29	-0.50

Table 3: Metal Commodity Demand Model Elastiticites

Appendix B

The trend break test is based on a vector autoregression (VAR) of the form:

$$y_t = \alpha + \sum_{i=1}^{4} A_i y_{t-i} + \varepsilon_t$$

where y_t is a vector containing the difference price and inventory series. This procedure tests whether there exists a date, γ, such that:

$$\alpha + A_j = \begin{cases} \alpha_1 + A_{j,1} & \text{for } t > \gamma \\ \alpha_2 + A_{j,2} & \text{for } t > \gamma \end{cases}$$

In other words, for every week in the data set, the data is split into two periods: the sample period before the selected week and the sample period after the selected week. We then estimate the coefficients in the VAR model using each sample period and test whether there is a statistically significant difference between the coefficients estimated using the two different samples. The week for which the difference in model parameters is most statistically significant is the structural break date.

Appendix C

The algorithm deals with supply shocks by using a time series model (VAR) to detect deviations from trend.[37] This VAR models current production, $prod_t$, as a function of lagged production values:

$$prod_t = \beta + \sum_{i=1}^{12} B_i prod_{t-i} + \varepsilon_t$$

We then compare the model's predicted production to actual production. Large differences between predicted and actual production indicate an unanticipated production shock.

[37] *See* James Stock & Mark Watson, *Vector Autoregressions*, 15 Journal of Economic Perspectives 101 (2001).