THREE ESSAYS IN COMMODITY RISK MANAGEMENT

by

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Abstract

This thesis includes three essays. These essays focus on the commodity market and cover a wide range of topics. Their topics range from the roles of inventory, pricing strategies to impacts of government policies on the commodity market.

The first essay provides an analytical framework to distinguish the roles of inventory by investigating their behaviors in a frequency domain. If inventory was used as a buffer for demand shocks, then the stock level should decrease at all frequencies under both the production smoothing and the stockout avoidance strategies. The inventory investment is negative at all frequencies under the stockout avoidance strategy while it is negative at high frequencies (short-term) and is positive at low frequencies (long-term). On the other hand, if inventory is used as a speculative tool, then its level and the inventory investment should increase with the increases in demand and prices at all frequencies. The volatilities of inventory investment also reveal the roles of inventory. Under production smoothing theory, inventory investment is as volatile as the demand at all frequencies while it is as volatile as the output if growth is persistent but less volatile than output if growth is not persistent. The crude oil inventory at the aggregate level followed the inventory the smoothing motive in the period of flexible production from 1/1931 to 12/1972 and the stockout avoidance motive during the period of restricted production from 1/1973-12/2012. The oil inventory at Cushing exhibits a speculative characteristic. However, trading inventory at Cushing did not have effects on price. Price was determined by supply and demand at the aggregate level.

The second essay studies role pricing strategies in the price discovery process through a supply chain, especially in the case of stainless steel. Full cost pricing is shown to connect the component costs to the product price. The surcharge system employed by stainless steel

industry has linked nickel price, the major component cost, to the price of stainless steel. The reason that nickel but other components played a key role in determining the movement of stainless steel price was its volatility. Nickel futures market also helps guide the price discovery process and production planning of stainless steel. Nickel futures provide a tool to manage stainless steel risk since they are proven to be the accurate predictors of stainless steel prices under different loss functions compared to no-change forecast in most of our real-time data tests after accounting for shift in relationship of nickel and stainless steel over time.

The third essay studies the impacts of government interventions on the commodity market, specifically steel contracts. The interventions from the Chinese government provided an interesting natural experiment on the futures market in which two different steel contracts, reinforced bar (rebar) and hot rolled coil (HRC), both reflected the same fundamentals but were subjected to different degrees of regulations. These interventions impacted trading activities and market quality of both contracts. The intervention mechanism shows that the deteriorating market quality of the HRC was the result of increasing volatility stemming from the speculation of government intervention in the rebar market. Speculative activities led to stronger comovement between these two contracts and less informative prices. We also found evidence of informed trading activities in the market. Higher trading volume and lower open interest indicate the occurance of an intervention announcement in the next day.

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Chapter 1

Roles and Behaviors of Commodity Inventories

This paper provides an analytical framework for distinguishing the roles of inventory by investigating their behaviors in a frequency domain. If inventory was used as a buffer for demand shocks, then the stock level should decrease at all frequencies under both the production smoothing and the stockout avoidance strategies. The inventory investment is negative at all frequencies under stockout avoidance strategy while is negative at high frequencies (short-term) and is positive at low frequencies (long-term). On the other hand, if inventory is used as a speculative tool, then its level and the inventory investment should increase with the increases in demand and prices at all frequencies. The volatility of inventory investment also reveal the roles of inventory. Under production smoothing theory, inventory investment is as volatile as the demand at all frequencies while it is as volatile as the output if growth is persistent but less volatile than output if growth is not persistent. The crude oil inventory at aggregate level followed the inventory the smoothing motive in the period of flexible production from 1/1931 to 12/1972 and stockout avoidance motive during the period of restricted production from 1/1973-12/2012. The oil inventory at Cushing exhibits a speculative characteristic. However, trading inventory at Cushing did not have effects on price. Price was determined by supply and demand at aggregate level.

1.1 Introduction

The roles of inventory, whether consumer goods or commodity inventory, have been studied extensively for a quite some time. The recent development of commodity prices as of the beginning of this century have reignited the interest in examining the roles of inventory. While many researchers pointed to the accumulation of inventory in conjunction with the rising price as the evidence of speculation for either financial gain or demand (Kilian and Murphy, 2014; Dvir and Rogoff, 2014), others were skeptical (Knittel and Pindyck, 2016), or even disagreed (Geman and Ohana, 2009; Kucher and Kurov, 2014). The conflicting conclusions have raised the question: Does increasing inventory accompanied by rising price and demand always mean speculation? Thus, the goal of this paper is to answer that question by providing an analytical framework to distinguish the roles of inventory by looking at its behaviors across time horizons through the frequency domain.

Understanding the roles of inventory is important because they contain information about the supply and demand fundamentals. Inventory behaves in different ways when it takes on different roles. However, inventory may sometimes act in a similar manner while assuming different functions, and that probably is the reason why we see inconsistencies in the conclusions of the roles of inventory in the literature. Wen (2005) shows that inventory investment moves differently in the short-term and the long-term. Hence, to capture a whole picture of inventory movement under a certain role, it is necessary to examine both the stock level and the inventory investment which is the difference in inventory between two periods. Inventory could be used to either facilitate production and consumption, such as smoothing production cost and avoiding stockout, or to speculate for financial gain. If inventory was meant to be used as a speculative tool, then the stock level and the inventory investment should increase whenever demand and price grow, regardless of time horizon. Some may argue that speculation is often carried only for a short span of time only because it is risky to speculate over an extended period, and hence we will only see inventory rises in the short horizon but not the long run (Beidas-Strom and Pescatori, 2014). However, if price continues to rise, arbitrageurs can roll-over their hedging positions, and therefore, inventory should increase in the long run as well. On the other hand, if inventory is used as a buffer, firms will draw from their stocks to satisfy any unexpected demand. Hence the stock level always goes down when demand and price rise. Specifically, when inventory is used to smooth production cost, firms will consistently produce at their optimal level and use their inventories to accommodate any excess demand. Thus, we will see the stock level, and the inventory investment always decrease when demand and price go up. And in the case of stockout avoidance, firms choose to produce a constant safety stock amount above the expected demand and put that in inventory to avoid stockout if there is any shock in the demand. In this case, firms' production capacities are often restricted in short run, and they cannot expand their output to satisfy the demand shock; hence inventory will be drawn to satisfy the excess demand. However, firms have time and resources to expand their capacities in the long run. Thus the firm would likely invest more in inventory to avoid stockout when demand and price continues to rise. Therefore, the increase in inventory, in this case, does not mean that inventory is used for the purpose of speculation.

Besides that, the volatility of inventory could also help explain its role. When the inventory was used to speculate, inventory will grow (shrink), following the changes in demand. Thus inventory will be as volatile as demand. On the other hand, when the firm engages in production smoothing, and if demand shock is not too high, it will always produce at its optimal level, and inventory will vary depending on the fluctuation of demand. Hence, inventory variance will be larger than production variance but not higher than demand variance at all time horizons. However, when the demand shock is high above the firm's optimal production level, it will expand its production just enough to fulfill the demand and keep inventory close to zero. If this occurs frequently with the probability of 50 percent or higher, as shown in the proof in the next section, then the inventory investment will be as varied as production and demand. Under the stockout avoidance, inventory is more volatile than demand and output in the short run since firms continuously draw from stocks to meet demand shocks. In the long term, firms are able to expand their capacities and are less reliable on inventory to satisfy fluctuating demand. Consequently, inventory will be less volatile than production and demand in the long-run.

Therefore, inventory needs to be observed at different time horizons in order to capture the whole picture of its behavior and to understand its role better. To conceptualize the above intuitions, the results of canonical inventory models will be put into the frequency domain for examination. The analytical framework proposed here could apply to any commodity. However, crude oil was chosen to analyze the proposed theory in this study because of its consumption and investment properties, as well as its unique supply characteristics. Unlike many other commodities that are produced periodically such as agriculture products, oil is produced continuously. Hence, it is unlikely to rely on crude oil inventory to serve as a source of supply. The crude oil market is also very different from corn, wheat or metals in that it tends not to be stored above ground in abundance (leaving it in the ground is much cheaper), and what has been produced tends to be consumed relatively quickly, leaving little in the way of excess stocks. At any point in time, crude oil inventories in the United States may be about 20 or 34 days worth of consumption, whereas immediately after the corn harvest there is enough corn inventory to supply the United States for the entire upcoming year.[1]

This paper is structured as follows: Section 2 will review the roles of crude oil inventory in the literature. Following that, Section 3 will present the inventory model and analytical approach to substantiate the differences in behaviors of inventories among different roles. Inventory will be examined under frequency domain to illustrate its behavior in the short-term (high frequencies) and long-term (low frequencies). In Section 4, we will discuss the empirical framework to examine the results of inventory models. Baxter-King (BK) bandpass filter was used to separate high frequencies from low frequencies of inventory, price, supply and demand, and the cointegration test; and the vector error correction model (VECM) was then applied to verify their relationship at different frequencies. Finally, Section 5 will provide conclusions and discussion about the findings.

1.2 Literature review

There are two strands of the literature which provide different views regarding the role of crude oil inventory. One strand of the research is concerned about the speculative character of oil inventory while the other is skeptical about the speculative role and believes that inventory is used as a buffer against excess demand.

[1] US Total Petroleum Consumption. US Energy Information Administration.
Supply and Demand Review. US Department of Agriculture.

The rising levels of crude oil inventory are interpreted as a sign of speculative pressures in the oil market (Hamilton, 2009). Some claimed that the price surge was the result of the speculative position of hedge funds. Buyuksahin et al. (2009) reported that the investments linked either to the Goldman Sachs Commodity Index or to one of five prominent commodity indices exceeded \$140 billion compared to \$5 billion in 1999. Also, according to The Bank for International Settlement data, trading in both registered commodity exchanges and OTC markets has increased sharply since 2005. The number of outstanding derivative contracts on commodity exchanges increased from 12.7 million contracts in March 2002 to 47 million contracts in 2008. The rising levels of commodity trading, in conjunction with rising prices, were suggested as a sign of speculative demand pressure in markets. This argument asserted that a large amount of investor's demand for long positions drove up commodity futures prices, then higher futures prices would signal the expectation of rising spot prices and hence drove up the demand for oil inventories above the ground. Ederington et al. (2012) presumed the existence of financial speculation on the spot price by uncovering the significant positive correlation between crude oil inventories at Cushing, a WTI pricing and physical settlement hub, and the spread between the two- and one-month WTI crude oil futures over the 2004-2011 period. However, Ederington et al. failed to recognize the inverted condition of the market during that period. The inverted phenomenon is that a nearby futures contract is priced at a higher price compared to a distant futures contract. For most of the time from 2000 to 2009, the prices of 12-month oil contracts are lower than prices of 6-month contracts and those of 6-month contracts are lower than prices 3-month contracts. Inverted market prevents hedgers from holding on to their inventories, since each time the hedge is rolled forward, the market will penalize them by offering a lower price. Moreover, money that flowed into futures markets should not be equated with demand for physical commodities because futures contracts could be settled for cash (Hieronymus, 1977). Financial traders participate in futures markets which consist of purely financial transactions. These financial traders do not take or make physical deliveries and hence do not participate in spot markets where long-term price equilibrium is determined (Garbade and Silber, 1983).

Others argue that rising levels of inventories are evident of speculative demand pressures rather than pure financial speculations. Alquist and Kilian (2010) assumed that unobservable shifts in expectations about future oil prices must be reflected in shifts in demand for above ground storage of crude oil. If there were speculation in oil futures market, it would have caused speculative demand for inventories to shift. Therefore, the information contained in oil futures prices is already contained in changes in inventory levels, and changes in the aboveground oil inventories are sufficient statistics for the information on the oil futures spread.[2] Based upon that assumption, there are several papers empirically examining the relationship between inventories, supply, demand, and prices of crude oil. These studies are based on structural vector autoregressive (SVAR) models to disentangle the effects speculative shocks, the supply and demand shocks on oil prices (Baumeister and Peersman, 2013; Kilian and Murphy, 2014; Beidas-Strom and Pescatori, 2014). Kilian and Murphy (2014) proposed a structural vector autoregressive (SVAR) model with restrictions on signs of the impact responses of four variables to each structural shocks. Those responses include a flow of supply, a flow of demand, a speculative demand which is defined as an increase in inventory, and residual demand shocks which are unexplainable by other shocks mentioned previously. They found episodes of speculation occurring in 1979, 1986, 1999/2000, 2007. However, speculative demand played a modest role in price increases during the 2007-2008 period compared to earlier periods; and the sustained run-up in oil price was caused primarily by shifts in the global demand for oil. Contrarily, Beidas-Strom and Pescatori (2014) found a larger effect of speculation demand by imposing additional restrictions to the range of impact of speculation factors from the Kilian and Murphy model. They argued that anomalies in the futures market are temporary, hence financial speculation can increase the short run oil price volatility, but it should contribute little to the low frequency fluctuation. By confining speculative demand to a short duration, and restricting its long-term effects, the increase of oil prices during 2003-2008 was shown to be driven initially and solely by a flow of demand but later was joined by speculative shocks from 2005 onward. The problem for all of the models using SVAR is that all variables are regarded as endogenous and, hence their values should be generated endogenously by the model and not be forced upon them exogenously. In reality, there could be cases where one or more of

[2]See discussion in Giannone and Reichlin (2006)

the variables are exogenous and not affected by feedback relations within the system under consideration. In such cases a conditional analysis, as described in the preceding, is plausible. From a different angel, Dvir and Rogoff (2014) extended upon the inventory model of Deaton and Laroque (1996) to account for exogenous shifts in income. They found that inventory and price move in an opposite direction when the oil supply is flexible, but this relationship reverses when supply is inflexible. In the case of unrestricted supply, as the income rises above its long-run level, production will increase to accommodate higher demand. However, income will revert back to its trend, and hence rational agents will sell some of their inventories before price drops in order to take advantage of the relative high price, resulting in low inventories. On the other hand, when supply is restricted, a rise in income will not induce a rise in production or any mean reversion. Therefore, increases in price due to increases in demand can be seen as a process that is likely to continue, causing rational agents to accumulate inventories. The authors went on to test for the cointegration relationship between storage, availability (supply + inventory from last period), income, and price and then estimated a cointegration vector between those factors for periods of 3/1931-12/1972 and 1/1975-12/2011. The cointegration relationships were found in both periods using data from OECD. While the equilibrium relationship between storage and price estimated from the cointegration vector is negative in the first period, it becomes positive in the second period. Therefore, increases in price will signal further price increases in the future which eventually will lead to an accumulation of stock in order to avoid the price hike.

On the other hand, may researchers expressed their doubt about the speculative role of crude oil inventory. Knittel and Pindyck (2016) developed a theoretical aggregate supply demand model of oil storage to examine claims of speculation in the oil market from the period of 01/2007 to 04/2011. In their study, the counterfactual prices and inventories are calculated for the case of no speculative activities, and are compared with actual prices and inventory levels. The result showed that the actual level of inventory changes were much smaller in magnitude than it would be if price changes were completely due to speculation. The mean of implied inventory change is nearly 600 million barrels compared to the mean of 1.62 million barrels of actual inventory change. Thus, the authors ruled out speculation as an explanation for sharp changes in oil prices. Moreover, inventory was assumed to have a buffer role when it was shown to have a positive correlation with price spread when inventory level is low but did not present when inventory was abundant (Geman and Ohana, 2009; Kucher and Kurov, 2014).

1.3 Inventory model

1.3.1 Inventory as a buffer

Inventories play an important role in facilitating production and consumption. There are many reasons to hold an inventory. Producers hold inventories to facilitate production and to avoid stock out. Since, producers face capacity constraints, inventories are are built up on the anticipation of future consumption. Producers also maintain their inventories as buffers to avoid stockout in the event of fluctuating demand. On the other side, consumers also hold inventories to smooth their consumption, and to avoid stockout. Like producers, consumers build up inventories to cushion the seasonal spike in consumption as well as any uncertainty in supply that could lead to stockout and disrupt productions. Producers, consumers, and arbitragers are all facing the same utility maximization problem which they have to determine the levels of current and future consumption to maximize their profits. The profit maximization model presented below will apply for all the aforementioned agents and will be used to study the production smoothing and stockout avoidance motives.

Consider the market for commodities that consists of producers, consumers whose excess demand for commodity depends only on the current price p_t, and inventory holders, or speculators who carry forward the commodity from one period to the next. For convenience, producer, consumer and speculator will be referred as a firm. Assume that the firm faces a demand θ_t which is a stationary AR(1) process:

$$\theta_t = \gamma + \rho \theta_{t-1} + \varepsilon_t \tag{1.1}$$

where ε_t is an i.i.d. random variable with normal distribution $N(0, \sigma^2)$.

The production in period t is y_t and the inventories holding at the beginning of period t, denoted s_{t-1}, is the inventory at the end of the last period. If the price is sufficiently high enough, and if realized demand is much higher than production, then the maximum amount that the firm can sell in period t is its inventory as of the end of the previous period plus the amount it produces during period t. Otherwise, if realized demand turns out to be lower than production during period t, then the actual sales will be equal to the demand. Assume that the price p is sufficiently high, we have

$$z_t = \min\{\theta_t, s_{t-1} + y_t\} \tag{1.2}$$

where z_t denoted actual sales in period t.

We also assume that the production decision is made one period ahead. Hence, the production decision for y_t needs to be made one period in advance based on the information available in the period $t-1$. The cost of production is a function of production quantities $c(y_t)$, where $c' > 0, c'' \leq 0$ and a_t is a stationary AR(1) process representing cost shock at period t.

$a_t = \phi + \rho_a a_{t-1} + v_t$

where $-1 < \rho < 1$.

Profits the firm could make in period t are simply revenue minus cost, $p_t z_t - a_t c(y_t)$, of which p_t is the selling price in period t. The price p_t can be written as the inverse function of consumption and demand shock $p_t = P(z_t, \varepsilon)$

The problem for the firm facing is to choose production and inventory holding in each period to maximize their profit.

$$\max_{\{y_i\}} E_{t-1}\left\{\max_{\{s_i\}} E_t\left\{\sum_{i=t}^{t+1} \beta^{i-t}\left[p_i z_i - a_i c(y_i)\right]\right\}\right\}$$

subject to

$$z_t + s_t = s_{t-1} + y_t \tag{1.3}$$

$$s_t \geq 0 \tag{1.4}$$

where β is a one period discount factor and lies between 0 and 1. Equation 1.3 is the resource constraint which assumes that there is no lost due to storage. And (1.4) is a non-negative inventory constraint which guarantees that inventory will not drop below zero and expresses stock-out avoidance motive of a firm.

Denoting λ and π as the Lagrangian multipliers associated with the resource constraint and the non-negativity on inventory respectively, the first order conditions with respect to output and inventory holding are

$$c'(y_t)E_{t-1}a_t = E_{t-1}\lambda_t \tag{1.5}$$

$$\lambda_t = \beta E_t \lambda_{t+1} + \pi_t \tag{1.6}$$

In (1.5), the expected marginal cost of production equals the expected shadow good price (λ). In (1.6), the cost of increasing inventories by one unit is λ_t due to the lost opportunity for sale in period t, and the benefit for having one extra unit of inventories available for sale in the next period is the discounted next period price. The marginal cost for keeping one extra unit of inventories in period t must be adjusted by a complimentary slackness multiplier $\pi \geq 0$. Specifically, π is positive when stockout occurs and 0 when stockout does not occurs. In equilibrium, marginal costs equal marginal benefits.

1.3.1.1 Production smoothing

Assume that production is instantaneous and costs shocks are absent $(a_t = 1)$.

(1.5) can be written as

$\lambda_t = c'(y_t)$

and (1.6) can be written as

$$c'(y_t) = \beta E_t c'(y_{t+1}) + \pi_t \tag{1.7}$$

which shows the incentive for cost (or production) smoothing when the firm does not stockout (i.e. $\pi_t = 0$). If the expected lost from holding inventory, i.e. $\pi_t > 0$, it would be optimal to not carry inventory to the next period, hence $s_t = 0$. If there is no cost in holding inventory, i.e. $\pi_t = 0$, the speculator will demand positive inventory and bid up the price until current and expected future prices are equal. Thus, we consider two cases: case A when$\pi_t > 0$, $s_t = 0$ and case B when $\pi_t = 0$, $s_t \geq 0$.

Case A: $\pi_t > 0$ implies that demand is high and it is more costly to keep inventories inventory in this period than the next period, hence the firm prefers to utilize all of its production $s_t = 0$. The resource constraint 1.3 implies $y_t = z_t - s_{t-1}$ which means that production keeps track of sales when demand is above normal level.

Case B: $\pi_t = 0$ and $s_t \geq 0$. In this case, total demand is more than the demand for current consumption. And as it is shown byWen (2005), or by Deaton and Laroque (1992) in a similar fashion, the solution for (1.7) is $c'(y_t) = \eta$, where η is a constant, or $y_t = y^*(\eta)$, a production level at which a unit held into the next period would make zero expected profit. The resource constraint 1.3 implies $s_t = y^* + s_{t-1} - \theta_t$. The condition $s_t \geq 0$ gives the threshold level of demand shock as $\theta^* = y^* + s_{t-1}$, such that production is constant if $\theta_t \leq \theta^*$ and production is increasing in sales if $\theta_t > \theta^*$. Since a firm decides to produce at constant level in this case, the non-negative inventory requirement 1.4 might be violated when demand abruptly exceeds demand.

The optimal solution of the model can be summarized by the following decision rules.

$$y_t = \begin{cases} \theta_t - s_{t-1}, & \theta_t > \theta^* \\ y^*, & \theta_t \leq \theta^* \end{cases}$$

$$z_t = \begin{cases} y_t + s_{t-1} = \theta_t, & \theta_t > \theta^* \\ \theta_t, & \theta_t \leq \theta^* \end{cases}$$

$$s_t = \begin{cases} 0, & \theta_t > \theta^* \\ y^* + s_{t-1} - \theta_t, & \theta_t \leq \theta^* \end{cases}$$

Firms tend to employ production smoothing strategy when its production is flexible as shown in the decision rules. Firms will choose to produce at their optimal levels if the realized demand is lower than the productions at optimal levels, since firms' operating costs are lowest at those levels. Hence, the sales will be equal to the actual demands, and inventory at the end of that period will be equal to the difference of supply, production at the current period, the last period inventory, and sales. On the other hand, if the actual demand is higher than the optimal production level, firm will use its excess capacity to expand production to satisfy the demand shock. However, to keep its cost minimum, firms will produce just enough to cover the demand and carry no inventory. In this case, production is equal to the current demand subtract for last period inventory.

1.3.1.2 Stockout avoidance

When the firm's capacity is restricted, avoiding stockout and consumption disruption is a high priority. In this scenario, firms respond to demand uncertainty by imposing a non-negativity constraint on inventories in order to avoid stockout. To emphasize the stockout avoidance motive for holding inventories under demand shocks, cost shocks are assumed to be absent $a_t = 1$ and marginal cost is constant $c'(y_t) = c$ as in Kahn (1987) to rule out any production smoothing motive. Under these assumptions, 1.5 and 1.6 then become

$$E_{t-1}\lambda_t = c \tag{1.8}$$

$$\lambda_t = \beta c + \pi_t \tag{1.9}$$

An expectation operator E_{t-1} was applied on (1.9) to solve for the production decision rule based on the information available in period t – 1.

$$E_{t-1}\pi_t = (1-\beta)c > 0 \tag{1.10}$$

Equation 1.10 indicates, based on information available in period t – 1, the optimal expected inventory holding for period t must also be a non-negative constant, $E_{t-1}s_t = k \geq 0$, where k is an optimal cut-off point that determines whether the firm stocks out or not. Thus the decision rule for production is given by

$$y_t = k + E_{t-1}\theta_t - s_{t-1} \tag{1.11}$$

To determine actual inventory holdings in period t, consider the following two possible cases:

Case A: $\pi_t > 0$. In this case, the realized demand is high and the firm stocks out. Hence, we have the actual sales $z_t = k + E_{t-1}\theta_t - s_{t-1}$ and no inventory is left at the end of period t,$s_t = 0$.

Case B: $\pi_t = 0$. In this case, the realized demand is low and the firm incurs inventories, and now, actual sales exactly equal demand $z_t = \theta_t$ and inventory at the end of period t is $s_t = y_t + s_{t-1} - \theta_t = k - \varepsilon_t$, a difference between the amount that a firm plans to stock in their inventory and the market demand shock. The second equality is based on the decision rule for output and the law of motion for demand shocks. The requirement of non-negative inventory $s_t \geq 0$ implies that $\varepsilon_t \leq k$.

The equilibrium decision rules of the model can thus be summarized as follows

$s_t = \max\{0,\, k - \varepsilon_t\}$

$y_t = \gamma + \rho\theta_{t-1} + \min\{k,\, \varepsilon_{t-1}\}$

$z_t = \gamma + \rho\theta_{t-1} + \min\{k,\, \varepsilon_t\}$

Under stock out avoidance strategy, the firm's capacity is inflexible and cannot be expanded instantaneously with demand. Thus, to avoid stockout, the firm will choose to maintain an optimal inventory level. If this optimal is larger than the previous period's demand shock, then the buffer stocks that the firm chooses will be equal to the last period shock. If the realized demand shock is higher than the consumption, it will be equal production plus the buffer amount, and no inventory will be left at the end of the period. However, if the demand shock is smaller than the buffer amount, then the sale will be equal to demand and inventory will be the difference between the buffer amount and the demand shock of the current period.

1.3.2 Inventory as a speculation

Inventory is considered to be acquired for speculative reasons if the decision to do so is based exclusively on the prospect of profiting from a price increase. Theory of storage by Kaldor (1939) introduced the convenience yield to explain the benefit of holding physical commodity rather than a paper futures contract. The holder of a commodity inventory earns a convience yield because readily available stocks allow them to respond more efficiently to unexpected supply and demand shocks.

$$f_{t-1,t} - p_{t-1} = c_s\left(t-1,t\right) - c_y\left(t-1,t\right) \tag{1.12}$$

where $f_{t-1,t}$ is the futures price at time t-1 with expiration t, $c_s(t-1,t)$ is the storage cost, $c_y(t-1,t)$ is the convenience yield

The size of the spread between futures and spot prices represents the convenience yield and acts as a trigger for arbitrage trades. When distortions occur in the link between spot and futures prices, the potential for resource misallocation and mismanagement of risk emerges. Arbitrageurs will take actions to exploit distortions by taking short (or long) positions in futures contracts while simultaneously buying or selling the product, which translates into moving products into (or out of) storage. Therefore, futures price spreads impact the supply of crude oil by stimulating inventory adjustments through cash-and-carry arbitrage activity.

$$f_{t-1,t} - p_{t-1} = s_t \tag{1.13}$$

Assume that futures prices reflect the spot price in the future which $p_t - p_{t-1} = \alpha + \beta\left(f_{t-1,t} - p_{t-1}\right)$, where α and β are constant and $\beta \geq 0$. Then the stocks in (1.13) can be rewritten as followed

$$s_t = \alpha' + \beta'\left(p_t - p_{t-1}\right) = \alpha' + \beta'(1-L)p_t \tag{1.14}$$

1.3.3 Inventory and price relationship

Since the price of a commodity and its demand are positively correlated, the relationship between inventory and price can be deduced from the connection between inventory and demand.

Proposition 1. *Stock level is negatively correlated with price at all frequencies under the production smoothing strategy.*

Proof. Denote $P = \Pr\left(\theta_t > \theta^*\right)$ as the probability that demand at time t is larger than the threshold demand, the cross spectrum of inventory level and consumption is given by

$$\begin{aligned}
S_{sz}(\omega) &= \sum_{h=-\infty}^{\infty}\sum_{\tau=-\infty}^{\infty} s_t(\tau)\cdot z_t(\tau+h)\, e^{-j\omega h} \\
&= P\times 0 + (1-P)\sum_{h=-\infty}^{\infty}\sum_{\tau=-\infty}^{\infty}\left(y^* + s_{t-1} - \theta_t\right)(\tau)\cdot\theta_t(\tau+h)\, e^{-j\omega h} \\
&= (1-P)\left[\sum_{h=-\infty}^{\infty}\sum_{\tau=-\infty}^{\infty} Ls_t(\tau)\cdot\theta_t(\tau+h)\, e^{-j\omega h} - \sum_{h=-\infty}^{\infty}\sum_{\tau=-\infty}^{\infty}\theta_t(\tau)\cdot\theta_t(\tau+h)\, e^{-j\omega h}\right] \\
&= (1-P)\left(e^{-j\omega}S_{sz} - S_{\theta\theta}\right) \\
&= \frac{-S_{\theta\theta}(\omega)}{1-(1-P)\, e^{-j\omega}}
\end{aligned}$$

Power spectrum of demand $S_{\theta\theta}(\omega)$ is always positive at any frequencies ω. Since, $P \leq 1$, and $0 \leq e^{-j\omega} \leq 1$ for all frequencies ω, the cross spectrum of inventory level and sales S_{sz} is always negative at all frequencies, i.e. inventory level is counter cyclical at all frequencies. Demand and price of commodities are positively correlated from the law of demand, hence inventory investment and price are negatively correlated at all frequencies.

□

Proposition 2. *Inventory investment is negatively correlated with price at all frequencies under the production smoothing strategy.*

Proof. Denote inventory investment as $i_t = s_t - s_{t-1}$. The relationship between inventory investment and sales is given by

$$i_t = \begin{cases} 0, & \theta > \theta^* \\ y^* - z_t, & \theta \leq \theta^* \end{cases}$$

Since cross correlation of a constant with any signal will be zero, the cross spectrum between inventory investment i and sales z is given by

$$
\begin{aligned}
S_{iz}(\omega) &= \sum_{h=-\infty}^{\infty}\sum_{\tau=-\infty}^{\infty} i_t(\tau)\cdot z_t(\tau+h)\, e^{-j\omega h} \\
&= P\times 0 + (1-P)\sum_{h=-\infty}^{\infty}\sum_{\tau=-\infty}^{\infty}\left(y^* - z_t(\tau)\right)\cdot\theta_t(\tau+h)\, e^{-j\omega h} \\
&= (1-P)\left[\sum_{h=-\infty}^{\infty}\sum_{\tau=-\infty}^{\infty} y^*\cdot\theta_t(\tau+h) - \sum_{h=-\infty}^{\infty}\sum_{\tau=-\infty}^{\infty} z_t(\tau)\cdot\theta_t(\tau+h)\, e^{-j\omega h}\right] \\
&= (1-P)\left[0 - \sum_{h=-\infty}^{\infty}\sum_{\tau=-\infty}^{\infty}\theta_t(\tau)\cdot\theta_t(\tau+h)\, e^{-j\omega h}\right] \\
&= -(1-P)\, S_{\theta\theta}(\omega)
\end{aligned}
$$

Since power spectrum of sales $S_{\theta\theta}(\omega)$ is always positive, then cross spectrum of inventory and sale $S_{iz}(\omega)$ is negative at all frequencies □

Under the production smoothing motive, the firm has an excess capacity and can accommodate any demand fluctuation in both the long term and the short term. Hence, it is more efficient for the firm to produce at its optimal level, and use its inventory or adjust its production rate when needed to buffer against demand shock. As demand increases, price rises, and inventory will be drawn down to meet the demand changes. However, both of the velocity S_{sz} and acceleration S_{iz} of inventory change with respect to prices are negative indicating that inventory is drawn down at an increasing speed when demand and price rise. This implies that firms rely heavily on inventory to manage their demand.

Proposition 3. *Stock level and price are negatively correlated at all frequencies under the stockout avoidance strategy.*

Proof. Denote L as the lag operator. The cross spectrum of inventory investment and sales in the two previous cases are

Case A: $\varepsilon_t > k$. The decision rules imply $z_t = \rho\theta_{t-1}$ and $i_t = 0$. Hence the cross spectrum of inventory investment and sales is zero at every frequency.

Case B: $\varepsilon_t \leq k$. The decision rules imply $z_t = \theta_t$ and $s_t = -(1-\rho L)\theta_t$. The cross spectrum of inventory investment and sales is thus given by

$$
\begin{aligned}
S_{iz}(\omega) &= \sum_{h=-\infty}^{\infty} \sum_{\tau=-\infty}^{\infty} s_t(\tau) \cdot z_t(\tau+h) e^{-j\omega h} \\
&= \sum_{h=-\infty}^{\infty} \sum_{\tau=-\infty}^{\infty} -(1-\rho L)\theta_t(\tau) \cdot \theta_t(\tau+h) e^{-j\omega h} \\
&= -\left(1-\rho e^{-j\omega}\right) S_{\theta\theta}(\omega)
\end{aligned}
$$

Since spectrum of demand $S_{\theta\theta}(\omega)$ is always positive, and $\rho e^{-j\omega}$ is always smaller than 1 for all frequencies ω, the cross spectrum of stock level and sales is always negative at any frequency. □

Proposition 4. *Inventory investment and price are negatively correlated at high frequencies* $(\omega \geq \pi/2)$ *and only positively correlated at low frequencies* $(\omega \leq \pi/4)$ *when demand growth is persistent* $(i.e., \rho > \frac{2}{\sqrt{2}} - 1)$ *under stockout avoidance strategy.*

Proof. It was shown by Wen (2005) in similar fashion that under the stockout avoidance motive the inventory investment is pro-cyclical for $\omega < \pi/4$ and counter-cyclical for $\omega \geq \pi/2$. Frequency $\pi/2$ and $\pi/4$ corresponds to 2 and 4 months per cycle respectively. Denote L as the lag operator and $i_t = s_t - s_{t-1}$ as inventory investment. The cross spectrum of inventory investment and sales in the two previous cases are

Case A: $\varepsilon_t > k$. The decision rules imply $z_t = \rho\theta_{t-1}$ and $i_t = 0$. Hence the cross spectrum of inventory investment and sales is zero at every frequency.

Case B: $\varepsilon_t \leq k$. The decision rules imply $z_t = \theta_t$ and $i_t = \varepsilon_{t-1} - \varepsilon_t = (L-1)\varepsilon_t = (L-1)(1-\rho L)\theta_t$. The cross spectrum of inventory investment and sales is thus given by

$$
\begin{aligned}
S_{iz}(\omega) &= \sum_{h=-\infty}^{\infty}\sum_{\tau=-\infty}^{\infty} i_t(\tau)\cdot z_t(\tau+h)\,e^{-j\omega h} \\
&= \sum_{h=-\infty}^{\infty}\sum_{\tau=-\infty}^{\infty} -(1-L)(1-\rho L)\,\theta_t(\tau)\cdot\theta_t(\tau+h)\,e^{-j\omega h} \\
&= -\left(1-e^{-j\omega}\right)\left(1-\rho e^{-j\omega}\right)S_{\theta\theta}(\omega) \\
&= -\left(1+\rho e^{-2j\omega}-e^{-j\omega}-\rho e^{-j\omega}\right)S_{\theta\theta}(\omega) \\
&= [(1+\rho)\cos\omega-\rho\cos 2\omega-1]\,S_{\theta\theta}(\omega)-i\,[(1+\rho)\sin\omega-\rho\sin 2\omega]\,S_{\theta\theta}(\omega) \\
&= re(\omega)+img(\omega) \qquad (1.15)
\end{aligned}
$$

where $S_{\theta\theta}(\omega)$ is the power spectral density of demand. Since the power spectral density is always positive, we can ignore it without loss of generality. In (1.15), $S_{iz}(\omega)$ is composed of two parts, the real number $re(\omega)$ and the imagined number $img(\omega)$. Among those, the real part $re(\omega) = (1+\rho)\cos\omega - \rho\cos 2\omega - 1$, is proportional to the covariance between i and z at frequency ω. If $\rho = 0$, then the real part $re(\omega) = \cos\omega - 1 \leq 0$ for all ω. Therefore, without serial correlation in demand shocks, the correlation between inventory investment and sales can never be positive. The real part of $S_{iz}(\omega)$ is a increasing function in ρ since $\frac{\partial re(\omega)}{\partial\rho} = \cos\omega - 2\cos^2\omega + 1 > 0$ for all $\omega \in [0,\pi]$. Hence, it suffices to examine the function at its two extreme points $\rho = 0$ and $\rho = 1$.

For $\omega \in [\pi/2,\pi]$, $re(\omega) = (1+\rho)\cos\omega - 2\rho\cos^2\omega + \rho - 1 < 0$ since $\cos\omega < 0$ and $\rho < 1$ for all $\omega \in [\pi/2,\pi]$. In other words, within high frequency interval $\pi \geq \omega \geq \pi/2$, inventory investment is negatively correlated.

For $\omega \in (0,\pi/4]$, the real part of $S_{iz}(\omega)$ is a increasing function in ρ since $\frac{\partial re(\omega)}{\partial\rho} = \cos\omega - 2\cos^2\omega + 1 > 0$ for all ω. Hence, it suffices to examine the function at its two extreme points $\rho = 0$ and $\rho = 1$. We have $\cos\omega - 1 < re(\omega) < 2\cos\omega - 2\cos\omega$. Since $\cos\omega - 1 \leq 0$ and $2\cos\omega - 2\cos^2\omega > 0$ for any $\omega \in (0,\pi/4]$, there must exist a $\rho^* \in (0,1)$ such that $re(\omega) = 0$. Hence, the real part $re(\omega) > 0$ for any $\omega \in (0,\pi/4]$ if and only if $\rho > \rho^*$. It is known that demands and prices of commodities are positively correlated. Hence, the relationship between price and inventory investment would be negatively correlated at high frequencies but positively correlated at business cycle frequencies when demand is persistent. □

Under the stockout avoidance motive, the stock level is counter cyclical with sales at all frequencies. However, inventory investment and sales are negatively correlated at high frequencies and are positively correlated at low frequencies if the demand shocks are persistent ($\rho > \rho^*$). In other words, the speed of inventory changes, $S_{sz}(\omega)$, is negative but its acceleration, S_{iz}, is positive in long term. Intuitively, in the short term, when price rises above its equilibrium level, it signals a strong growth in demand. However, the production is inflexible and cannot be expanded at the same pace as the demand growth in the short run. Hence, inventory will be drawn down to buffer against the demand shock. On the other hand, the production is more flexible and firm has time to expand its capacity in the long run. Therefore, if the demand grows steadily and price is expecting to rise persistently in the long run, the firm would invest in expanding its production capacity to avoid stockout. Firms still rely on inventory to manage the demand but the pace of inventory draw down will decrease.

Proposition 5. *Stock level and price are positively correlated at all frequencies under speculation motive.*

Proof. The cross spectrum of stocks and price is

$$\begin{aligned} S_{sp} &= \sum_{h=-\infty}^{\infty} \sum_{\tau=-\infty}^{\infty} s_t(\tau) \cdot p_t(\tau + h) e^{-j\omega h} \\ &= \sum_{h=-\infty}^{\infty} \sum_{\tau=-\infty}^{\infty} (1-L) p_t(\tau) \cdot p_t(\tau + h) e^{-j\omega h} \\ &= \left(1 - e^{-j\omega}\right) S_{pp}(\omega) \end{aligned}$$

Since $S_{pp}(\omega)$ is always positive, $S_{sp}(\omega)$ is positive at all frequencies ω. □

Proposition 6. *Inventory investment is positively correlated with price at all frequencies under the speculation motive.*

Proof. Inventory investment under speculation motive is $i_t = s_t - s_{t-1} = (1-L)^2 p_t$

The cross spectrum of inventory investment and price is given by

$$\begin{aligned}
S_{ip} &= \sum_{h=-\infty}^{\infty} \sum_{\tau=-\infty}^{\infty} i_t(\tau) \cdot p_t(\tau+h) e^{-j\omega h} \\
&= \sum_{h=-\infty}^{\infty} \sum_{\tau=-\infty}^{\infty} (1-L)^2 p_t(\tau) \cdot p_t(\tau+h) e^{-j\omega h} \\
&= \left(1-e^{-j\omega}\right)^2 S_{pp}(\omega)
\end{aligned}$$

Since $S_{pp}(\omega)$ is always positive regardless of frequency ω, $S_{sp}(\omega)$ is positive at all frequencies ω. Hence, inventory investment and price are positively correlated at all frequencies. □

1.3.4 Inventory volatility

Proposition 7. *Under the production smoothing motive, the variance of inventory is larger than the variance of production for all frequencies if the chance of the actual demand being larger than the demand at the optimal production level is smaller than 50 percent and vice versa.*

Proof. Denote $P = P(\theta_t > \theta^*)$. Since s = 0 when $\theta_t > \theta^*$ and $y^*$is a constant, their cross-correlation with others and with themselves will be 0. Therefore, the power spectrum of output is given by

$$\begin{aligned}
S_{yy}(\omega) &= P \sum_{h=-\infty}^{\infty} \sum_{\tau=-\infty}^{\infty} \theta_t(\tau)\, \theta_t(\tau+h) e^{-j\omega h} + (1-P) \sum_{h=-\infty}^{\infty} R_{y^*y^*}(h) e^{-j\omega h} \\
&= P \sum_{h=-\infty}^{\infty} R_{\theta\theta}(h) e^{-j\omega h} = P S_{\theta\theta}(\omega)
\end{aligned}$$

and the spectrum of inventory is

$$\begin{aligned}
S_{ii}(\omega) &= P \times 0 + (1-P) \sum_{h=-\infty}^{\infty} \sum_{\tau=-\infty}^{\infty} z_t(\tau) z_t(\tau+h) e^{-j\omega h} \\
&= (1-P) \sum_{h=-\infty}^{\infty} \sum_{\tau=-\infty}^{\infty} \theta_t(\tau) \theta_t(\tau+h) e^{-j\omega h} \\
&= (1-P) S_{\theta\theta}(\omega) \qquad (1.16)
\end{aligned}$$

.

Thus, for all frequencies $\omega \in [0, \pi]$

$$\begin{cases} S_{ii}(\omega) \geq S_y(\omega) & \text{if } P \leq 0.5 \\ S_{ii}(\omega) < S_y(\omega) & \text{if } P > 0.5 \end{cases}$$

□

Intuitively, when the firm's optimal production level often falls behind the actual demand, then the firm needs to adjust its production rapidly to accommodate the excess demand and to satisfy the non-negativity constraint of inventory in 1.4. By chasing demand, the firm makes it production more volatile than its inventory. On the other hand, if the actual demand turns out to be lower than the firm's optimal production level the majority of the time, then the firm will keep it production constant; hence inventory will fluctuate as a result of changing demand. Therefore, inventory investment will be more volatile than production in this case.

Proposition 8. *Under the production smoothing motive, the variance of the inventory investment is less than or equal to the variance of the demand at all frequencies.*

Proof. It can be seen from 1.16 that the power spectrum of inventory investment is smaller than or equal to the power spectrum of the demand since $P \leq 1$. Hence, inventory investment is at most as volatile as the demand. □

Proposition 9. *Under stockout avoidance motive, inventory investment is more volatile than output at high frequencies but less volatile than output at the low frequencies.*

Proof. The power spectrum of inventory investment is

$$\begin{aligned}
S_{ii}(\omega) &= P\times 0+(1-P)\sum_{h=-\infty}^{\infty}\sum_{\tau=-\infty}^{\infty}(1-L)\varepsilon_t(\tau)\left(1-L^*\right)\varepsilon_t(\tau+h)\,e^{-j\omega h} \\
&= (1-P)\sum_{h=-\infty}^{\infty}(1-L)\left(1-L^*\right)R_{\varepsilon\varepsilon}(h)\,e^{-j\omega h} \\
&= (1-P)\left(1-e^{-j\omega}\right)\left(1-e^{j\omega}\right)\sigma_\varepsilon^2 \\
&= (1-P)\left(2-e^{-j\omega}-e^{j\omega}\right)\sigma_\varepsilon^2 \\
&= 2(1-P)(1-\cos\omega)\,\sigma_\varepsilon^2
\end{aligned}$$

where $P = Pr(\varepsilon_t > k)$, and $P \le 0.5$ since ε_t is a white noise and k is a positive constant.

Moreover,γ and k are constants, hence their crosscorrelations with others and with themselves will be zero. Additionally, crosscorrelation between white noise, ε_t and any time series will be equal zero. Hence, the power spectrum of output is given by

$$\begin{aligned}
S_{yy}(\omega) &= P\sum_{h=-\infty}^{\infty}\rho^2 R_{\theta\theta}e^{-j\omega h}+(1-P)\sum_{h=-\infty}^{\infty}\left(\rho^2 R_{\theta\theta}+2\rho R_{\theta\varepsilon}+R_{\varepsilon\varepsilon}\right)e^{-j\omega h} \\
&= P\rho^2\frac{\sigma_\varepsilon^2}{1-2\rho\cos\omega+\rho^2}+(1-P)\left(\rho^2\frac{\sigma_\varepsilon^2}{1-2\rho\cos\omega+\rho^2}+\sigma_\varepsilon^2\right) \\
&= \left[P\frac{\rho^2}{1-2\rho\cos\omega+\rho^2}+(1-P)\frac{1-2\rho\cos\omega+2\rho^2}{1-2\rho\cos\omega+\rho^2}\right]\sigma_\varepsilon^2 \\
&= \frac{\rho^2+(1-P)\left(1-2\rho\cos\omega+\rho^2\right)}{1-2\rho\cos\omega+\rho^2}\sigma_\varepsilon^2
\end{aligned}$$

It is easily seen that $S_{ii}(\omega)$ is monotonically increasing and $S_{yy}(\omega)$ is monotonically decreasing since $1-\cos\omega$ is decreasing and $1-2\rho\cos\omega+\rho^2$ is increasing in $\omega\in[0,\pi]$. Therefore, the ratio of inventory investment spectrum over the output spectrum,$S_{ii}(\omega)/S_{yy}(\omega)$, is a monotonically increasing function in ω. Hence, it suffices to consider the spectral density of inventory investment and output at the two extreme points $\omega = 0$ and $\omega = \pi$.

$$S_{ii}(\omega) = \begin{cases} 0 & \omega = 0 \\ 4(1-P)\sigma_\varepsilon^2 & \omega = \pi \end{cases}$$

$$S_{yy}(\omega) = \begin{cases} \left[\frac{\rho^2}{(1-\rho)^2} + (1-P)\right]\sigma_\varepsilon^2 & \omega = 0 \\ \left[\frac{\rho^2}{(1+\rho)^2} + (1-P)\right]\sigma_\varepsilon^2 & \omega = \pi \end{cases}$$

The ratio of inventory and output spectrum is

$$\frac{S_{ii}(\omega)}{S_{yy}(\omega)} = \begin{cases} 0 & \text{if } \omega\text{=0} \\ \frac{4(1-P)(1+\rho)^2}{\rho^2+(1-P)} & \text{if } \omega = \pi \end{cases}$$

The spectrum ratio is a decreasing function in ρ when $\omega = \pi$ and is bounded below by $\frac{16(1-P)}{2-P}$ at $\rho = 1$. The lower bound of the spectrum ratio is also decreasing and is bounded for $P \in [0, 0.5]$, hence its lower bound is 16/3.

As a results of the spectrum ratio $S_{ii}(\omega)/S_{yy}(\omega)$ being a monotonically increasing function, there would exist an $\omega^*(\rho, P) \in (0, \pi)$ such that $S_{ii}(\omega)/S_{yy}(\omega) < 1$ for $\omega \leq \omega^*$ and $S_{ii}(\omega)/S_{yy}(\omega) > 1$ for $\omega \geq \omega^*$. Therefore, the variance ratio is less than one at low frequencies and larger than one at high frequencies, suggesting that the inventory investment is less volatile in the short run and more volatile in the long run compared to out put. □

Proposition 10. *Under the stock out avoidance motive, inventory investment is more volatile than demand at high frequencies but less volatile than demand at low frequencies.*

Proof. The power spectrum of inventory investment and demand have been showed in previous section as

$$S_{ii}(\omega) = 2(1-P)(1-\cos\omega)\sigma_\varepsilon^2$$

$$S_{\theta\theta}(\omega) = \frac{\sigma_\varepsilon^2}{1-2\rho\cos\omega+\rho^2}$$

The ratio of the power spectrum of inventory investment and the power spectrum of demand is

$$\frac{S_{ii}}{S_{\theta\theta}} = 2\,(1-P)\,(1-\cos\omega)\left(1-2\rho\cos\omega+\rho^2\right)$$

It is clear that this ratio is a monotonically increasing function in $\omega \in [0,\pi]$ due to the fact that $S_{ii}\,(\omega)$ is an monotonically increasing function and $S_{\theta\theta}\,(\omega)$ is an monotonically decreasing in . It is sufficient to consider the ratio at its two extreme points.

$$\frac{S_{ii}(\omega)}{S_{\theta\theta}(\omega)} = \begin{cases} 0 & \text{if } \omega = 0 \\ 4\,(1-P)\,(1+\rho)^2 & \text{if } \omega = \pi \end{cases}$$

When $\omega = \pi$, the spectrum ratio of inventory and demand is an increasing function for $\rho \in [0,1)$ and is bounded below by $4(1-P)$ at $\rho = 0$. That lower bound is an decreasing for any $P \in [0,0.5]$ and is bounded below by 2 at $P = 0.05$.

Since the spectrum ratio is a monotonically increasing function in $\omega \in [0,\pi]$, there exists an $\omega^*\,(\rho,P) \in (0,\pi)$, such that $S_{ii}/S_{\theta\theta} \leq 1$ for $\omega \in [0,\omega^*]$, and $S_{ii}/S_{\theta\theta} > 1$ for $\omega \in (\omega^*,\pi]$. That implies that the variance of the inventory investment is smaller than the variance of demand at low frequencies but that relationship is reversed at high frequencies. Hence, the inventory investment is more volatile in the short run and less volatile in the long run compared to the demand. □

1.4 Empirical analysis

1.4.1 Cointegration and VECM

We are interested in examining the causal relationship among inventory investment, price and demand. The Granger causality test(1969) and VAR models are typically employed to examine the lead-lag relationships between factors. However, if any of the time series are not stationary, a regression of one on the other will appear to have a significant result, even if the series are completely independent. This phenomenon was first addressed by Granger and Newbold (1974) as a spurious regression. Differencing is a common method to create stationary. However, it is argued that differencing will eliminate information on any stable long-run relationships between the variables. Even though when time series exhibit a non-stationary behavior, they might have a common stochastic trend that is stationary (Engle and Granger, 1987). In other words, when the series are integrated which means they are non-stationary, and only stationary after differencing, then they should be tested for cointegration. The integrated series are called "cointegrated" if their weighted sum, called the cointegration vector, is stationary. The error correction model was proposed as a tool to emphasize the long-run relationships. The model involves current error in long-run relationships in levels, and describes how error set forth adjustments in the next period.

Johansen test provides an advanced framework for testing cointegration in multivariate system that allows for more than one cointegration relationship (Johansen, 1988; Johansen and Juselius, 1990). The Johansen tests are based on the eigenvalues of a stochastic matrix, and they have no bias. They seek the linear combination which is most stationary through a maximum likelihood, whereas the Engle-Granger tests seeks the linear combination having a minimum variance based on the ordinary least square. The relationship can be written in VAR(k) model as follows:

$$\Delta x_t = \sum_{j=1}^{k-1} \Gamma_j \Delta x_{t-1} + \Pi x_{t-1} + \varepsilon_t \tag{1.17}$$

where k is a $n \times 1$ vector of time series and each of which is $I(1)$ process; Γ_j and Π are $n \times n$ coefficient matrices measuring the short term and long term adjustments of the system to changes in x respectively.

If Π is equal to zero, this mean that there is no cointegration. If Π has full rank, then all x_t must be stationary. When Π has less than full rank but is not equal to zero, then it is a case of cointegration. Johansen and Juselius recommend the trace test for the rank number r of non-zero eigenvalues in Π

$$H_0 : r \leq R \quad \text{v.s.} \quad H_1 : r > R \tag{1.18}$$

$$Tr = -T \sum_{j=R+1}^{n} ln(1-\lambda_j) \tag{1.19}$$

where T is the sample size and n is the number of variables in the system. The eigenvalues of Π are real number such that $1 > \lambda_1 > ... > \lambda_n \geq 0$. The trace test involves testing a sequence of alternatives $r = 0$ against $r > 0$, $r \leq 1$ against $r > 1$, $r \leq 2$ against $r > 2$ and so on. Critical values of the Tr statistics can be found in Johansen and Juselius (1990).

The mechanism that ties the cointegrated series together is a causality in the sense that turning points of one series lead to turning points in the other (Granger, 1988; Covey and Bessler, 1992). In the case of cointegration, Π can be written as $\Pi = \alpha\beta'$, where α and β are $n \times r$ matrices. α can be interpreted as a "speed of adjustment towards equilibrium" and the causal flows of the cointegrated system can be revealed by building a vector error correction model (VECM) from (7)

$$\Delta x_t = \delta + \sum_{j=1}^{k-1} \Gamma_j \Delta x_{t-j} + \alpha(\beta' x_{t-1} + c) + \varepsilon_t \tag{1.20}$$

VECM shows variables adjusting to short run changes and deviation from equilibrium. α determines the direction of Δx_t, so that variable moves in the correct direction in order to bring the system back to equilibrium. In this study, the error term is determined by cointegration vectors of stock level or inventory investment ,and production, demand, and prices, i.e., $ect = s_{t-1} - \beta_1 y_{t-1} - \beta_2 \theta_{t-1} - \beta_3 p_{t-1}$, or $ect = i_{t-1} - \beta_1 y_{t-1} - \beta_2 \theta_{t-1} - \beta_3 p_{t-1}$. If any of the factors changes in a way that makes the error term positive, and if α is negative, then inventories, prices, or demand will change in the way that will reduce the error term in the next period and vice versa.

1.4.2 Data

This study look at the data at the aggregate level, as well as the local level where trading activities occur. At aggregate level, the monthly production and stocks data of crude oil used in this study were from the U.S. Department of Energy. These series were measured in million barrels and covered the period of January 1931 - December 2012. The crude oil price series reflected the West Texas Intermediate price delivered in Cushing, Oklahoma. Oil is used directly or indirectly by every sector of the economy; therefore, the demand for oil is commensurate with overall economic activity. The U.S. monthly total industrial production and capacity utilization index from Federal Reserve was used as a proxy for oil demand since it reflected a major economic activities in the U.S. At the local level, the stocks at Cushing, the delivery hub of NYMEX futures contracts. The demand at will be the refinery input and the export amount. Both the stocks and demand data at local level

Table 1.1: ADF tests for unit root

	Pre-1973		Post-1973	
	High Frequency	Business Cycle	High Frequency	Business Cycle
Stock	-4.857***	-4.461***	-4.840***	-4.129***
Inv	-11.184***	-7.297***	-11.938***	-8.250***
Production	-4.268***	-4.781***	-3.929**	-3.274.
Demand	-4.831***	-4.916***	-3.409.	-4.274***
Price	-3.155.	-4.168***	-1.314	-2.263

*** indicates that the null hypothesis of unit root or nonstationary can be rejected at the 1% level, ** the 5% level, * the 10% level.

were measured in thounsands barrels and at weekly frequency. This data starts from 2004 and can be obtained from U.S. Department of Energy.

These series were then filtered to extract the movements at high frequencies (short term) and low frequencies (long term). The high frequencies are from 2 to 4 months at aggregate level and 2 to 4 weeks at local level corresponding to $\pi/2$ to $\pi/4$ respectively in the previous section. The low frequency ranges are determined by the business cycles documented by the National Bureau of Economic Research. The business cycles, ranging from peak to peak, are from 32 tor 116 months for the period of 1/1931 to 12/1972 and from 18 to 128 months for the periods from 1/1973 to 12/2012. The selected frequencies will be a multiple of 12 month, so the the low frequency ranges will be 24 to 106 months for the period of 1/1931 to 12/1972 and 24 to 120 for the period of 1/1973 to 12/2012.

The filter applying to these data should be able to isolate a range of specified frequencies. Therefore, the choice of filter was the Baxter and King (1999) band-pass filter (B-K filter), since it not only allowed a cyclical component within a specified range of periodicity to be isolated as we wanted but also ensured that there is no phase shift in the output. All of the data series except for inventory investment were logged when applying the band-pass filter. The Augmented Dickey-Fuller tests for unit root of the filter series are shown in Table 1.1 on page 27. All of the filter series are stationary, except for the price series after 1973.

The filtered series of inventory investment, demand and price were plotted at high frequency and business cycle frequency for the flexible production period (before 1973) and restricted production period (after 1973) to illustrate the difference in inventory behavior.

Figure 1.1 on page 29 and Figure 1.2 on page 31 show the movements of the variables relative to their long run trends at different frequencies.

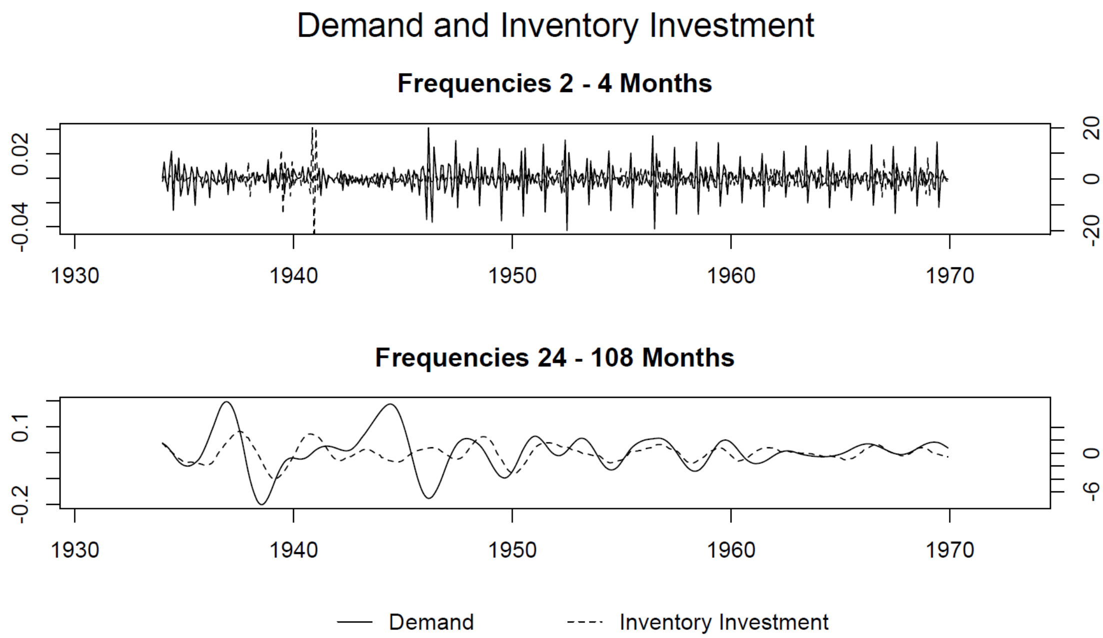
Figure 1.1 on page 29 shows that inventory investment of crude is lagging behind the demand and price of oil at both high and low frequencies. The large fluctuation in demand and price in the period from 1931 to 1950 are due to high demand and inflation of the recovery from the great depression. Following that was the period of 1955-1973 with extremely rapid growth in world oil output and consumption. The rates of growth of oil production and demand both were at 7 percent a year. Prices were also stable near $3 per barrel for this period. That is reflected through the flatter deviations of price, demand, and inventory investment from 1955 to 1972.

The year 1973 marks the beginning of the restricted production period and the shift in OPEC's power to influence oil prices with the 1973-74 oil embargo and the first oil price shock. Since 1973 there has been a dramatic reversal in production trends, particularly those of OPEC countries. During the period of 1974 to 1978, while non-OPEC production increased from 25 million barrels per day to 31 million barrels per day, OPEC kept its capacity and production relatively flat near 30 million barrels per day. 1.2 shows that at high frequencies, inventory investment is strongly counter cyclical with respect to demand and price. In contrast, at the business cycle frequencies, inventory investment seems to be procyclical with GDP. There are two periods, 1999 and 2007, on the graph where demand and inventory investment are moving in different directions at business cycle frequencies. Inventory investment lagging behind demand in 1999 was mainly caused by the miscalculations of OPEC. OPEC expanded its production just as East Asian countries were going into recession in 1997. The collapse of East Asia has created the glut of oil supply and sent oil price southwards. To correct that glut, OPEC then cut production in late 1999 just as East Asia was coming out of a recession. With supply falling, inventory investment could not keep up with rising demand, and price shot up. During the last three months of 1999 and the first three months of 2000 demand for crude oil was greater than supply by perhaps 2.5 million barrels a day.[3] The shortfall was filled by drawing down stocks. On the other hand, the long-run divergence of inventory and demand in 2007-2008 was caused largely

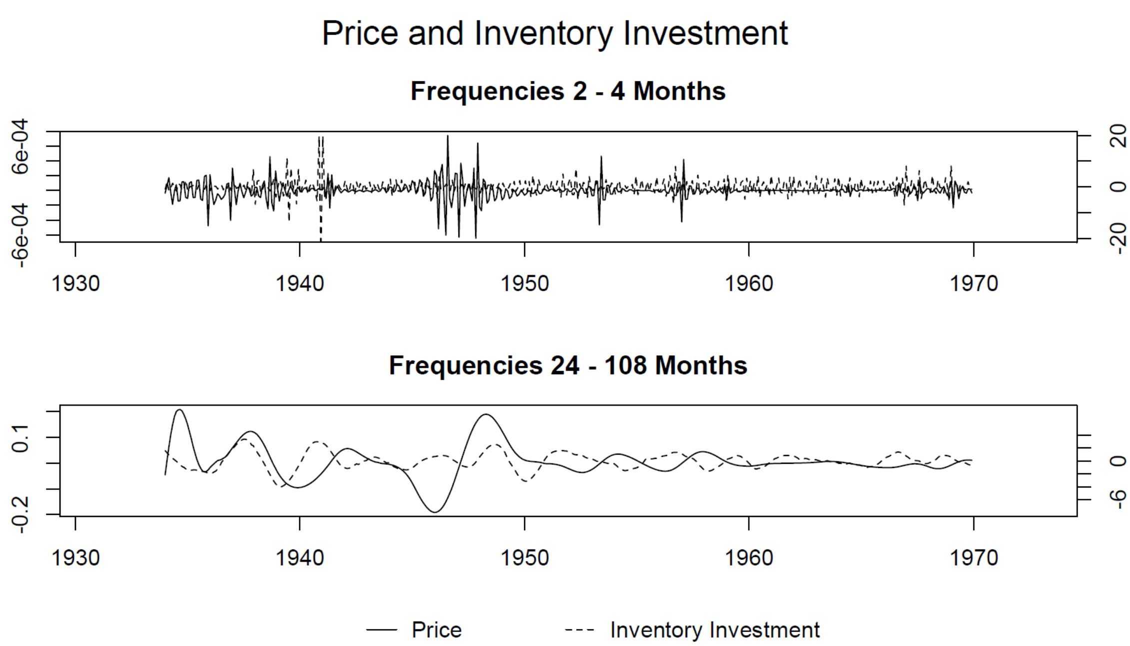
[3]Energy Information Administration (EIA), U.S. Department of Energy, Short-term Energy Outlook - March 2000, Table 3

Figure 1.1: Crude oil demand and inventory investment during the period 1931-1973.

(a) Demand



(b) Price



by strong consumption and flat supply. According to the International Monetary Fund , real gross world product grew by a total of 9.4 percent in 2004 and 2005.[4]On the other hand, the world production of petroleum, at 85 million barrels per day, was 5 million barrels per day higher in 2005 than in 2003, a 6 percent increase. Total U.S. production is now about half what it was in 1971.[5] Saudi production for 2007 was about 850,000 barrels a day lower than it had been for 2005.

Inventory investment and price on the other hand exhibit a reverse relationship. At high frequencies, inventory investment shows positive comovements with price most of the time. However, it displays a negative relationship with price at business cycle frequencies.

Isolating business cycle frequencies from high frequencies not only helped to understand the role of inventory but it also helped to detect changes in the fundamental. Inventories supposedly raise and fall with demand in the long term. However, Figure 1.1 on page 29 shows that this relationship was broken in 1999 and during 2004-2008. These divergences in inventory and demand signal the shortages in supply in 1999 when OPEC made a wrong move in cutting production, and in the period of 2004-2008 when oil production failed to keep up with growing demand. Similarly, inventories are expected to drop when price is high and vice versa. Nonetheless, inventory changed its course and raised with price for the period of 2004-2008.

1.4.3 Empirical results

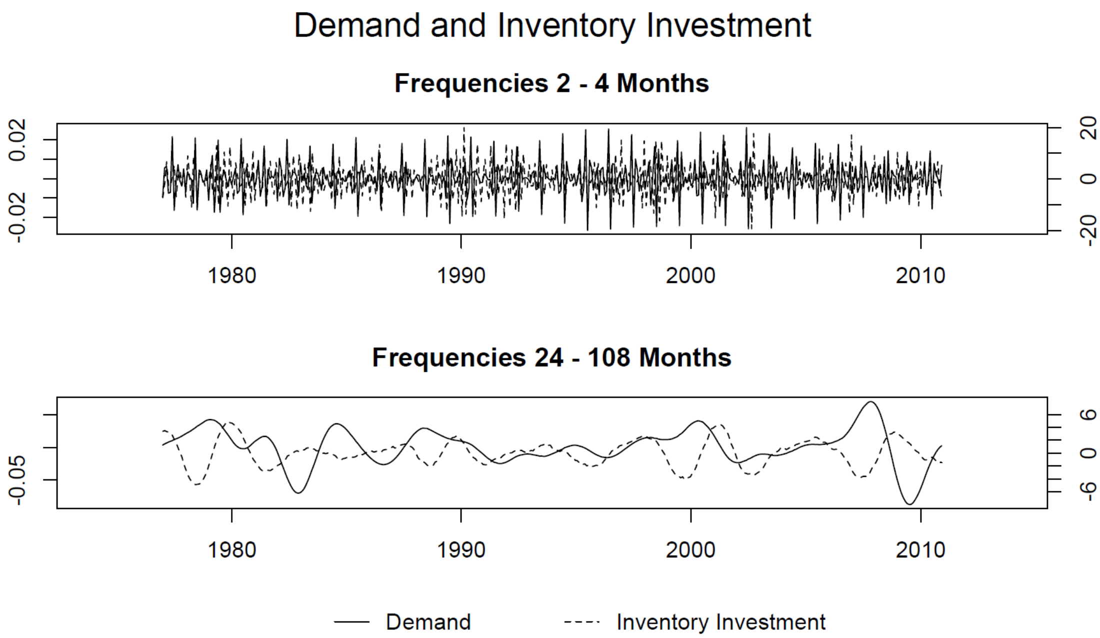
We first test whether a stationary cointegrating vector exists as predicted by the model at both high frequencies and business cycle frequencies. Table 1.2 on page 32 presents the results of Johansen trace tests conducted on both ranges of frequencies for the stock level and the inventory investment. The number of lags using in Johansen cointegration test is determined by the Schwarz-Bayes criterion since it is considered to be the most accurate for VECM (Ivanov and Kilian, 2005). It shows that the null hypothesis of no cointegration vector (rank zero) is strongly rejected in both cases at high frequencies and low frequencies.

[4]World Economic Outlook: October 2008, table A1

[5]EIA, U.S. Department of Energy, Monthly Energy Review, Table 11.1b

Figure 1.2: Crude oil price and inventories investment during the period 1974-2013

(a) Demand



(b) Price

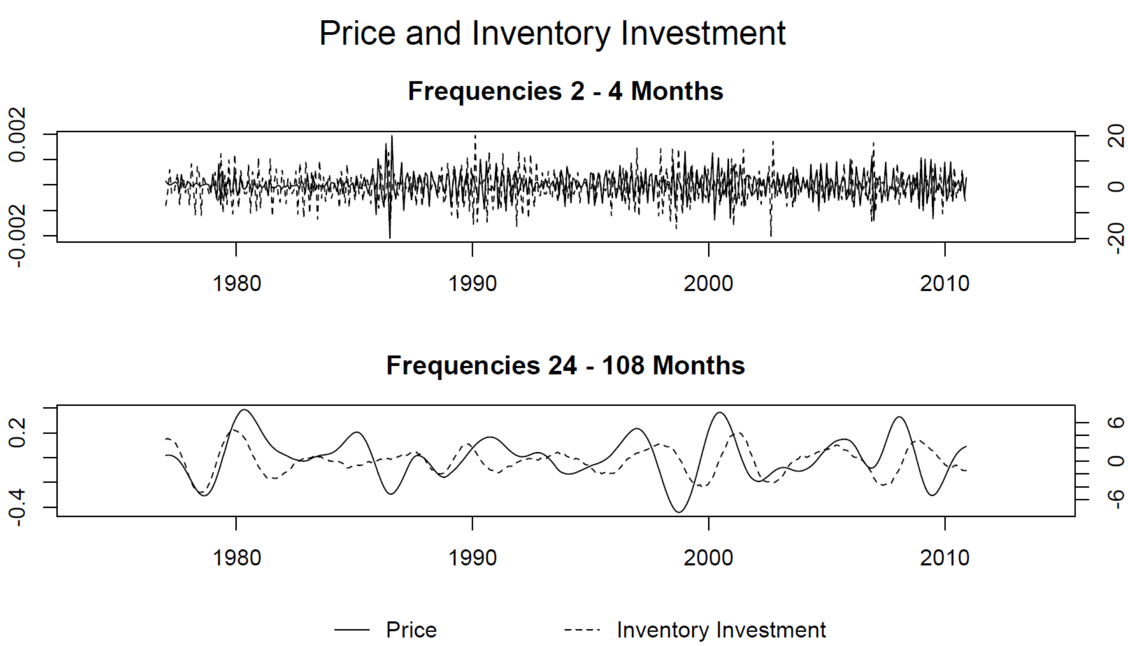


Table 1.2: Cointegration tests of stock level

		Stocks		Inventory investment	
		High Frequency	Business Cycle	High Frequency	Business Cycle
Pre-1973	$r <= 3$	10.27**	10.01**	11.11**	9.46**
	$r <= 2$	25.84***	26.08***	30.32***	37.26***
	$r <= 1$	55.55***	63.39***	72.19***	74.21***
	$r = 0$	133.02***	118.47***	227.54***	143.02***
Post-1973	$r <= 3$	8.15*	9.72**	5.31	8.92**
	$r <= 2$	25.54***	31.87***	19.77**	33.28***
	$r <= 1$	43.53***	58.89***	40.17***	59.82***
	$r = 0$	92.95***	105.10	228.95***	105.83***

'***' Indicates that the null hypothesis of no cointegration can be rejected at the 1% level, '**' the 5% level, '*' the 10% level.

From these tests, it can be concluded that there are common stochastic trends among the factors at each range frequencies respectively. The common stochastic trends are the cointegration vectors that link stock, or inventory investment with production, demand, and price all together. The vectors that connect those aforementioned factors at both frequencies were estimated using VECMs and were presented in the Table 1.3 on page 33 and Table 1.4 on page 34.

Table 1.3: MLE estimates relationship of stock level, production, demand, and price

		Pre 1973		Post 1973	
		High Frequency	Business Cycle	High Frequency	Business Cycle
α	stock	-2.767***	-0.002***	-2.966***	-0.004**
		(0.352)	(4.73e-04)	(0.515)	0.001
	production	0.185	8.17e-05	-0.399	-0.001
		(0.412)	(6.06e-04)	(0.285)	0.001
	demand	0.005**	1.23e-05***	8.58e-04	5.47e-06***
		0.002	(2.64e-06)	(7.01e-04)	(1.55e-06)
	price	-0.002	3.14e-06	0.017***	5.49e-05***
		(0.002)	(2.73e-06)	(0.004)	(1.04e-05)
β	stock	1	1	1	1
		(NA)	(NA)	(NA)	(NA)
	production	-1.357***	-2.514***	0.212	0.606
		(0.201)	(0.475)	(0.314)	(0.422)
	demand	-40.602***	-131.169***	-97.298·	-83.090
		(12.027)	(29.836)	(48.942)	(70.499)
	price	-34.441***	-83.538***	-49.108***	-75.546***
		(10.542)	(26.611)	10.094	(12.003)

'***' Indicates that the null hypothesis that the coefficient is equal to zero can be rejected at the 0.1% level, '**' the 1% level, '*' the 5% level, and '.' the 10% level.

Table 1.3 presents the results from an estimation of VECMs for stock level of crude oil using the maximum likelihood method under the restriction to one cointegrating vectors. The estimated cointegrating vector of stock level is $s_{t-1} = -1.375y_{t-1} - 40.602\theta_{t-1} - 34.441p_{t-1}$ at high frequencies and $s_{t-1} = -2.514y_{t-1} - 131.169\theta_{t-1} - 83.583p_{t-1}$ at low frequencies for the period before 1973 indicating a negative equilibrium relationship of crude oil stock with production, demand, and price at both frequencies ranges. It is clear that inventory is drawn down faster in the long term since coefficients of demand and price at low frequencies than at high frequencies. Moreover, the speed adjustment of the stock level at high frequencies and low frequencies are -2.767 and -0.002 respectively indicating that when the demand and prices are high relatively to their equilibrium values, inventory will be draw down to satisfy excess demand. This finding can also be confirmed by the VECM of changes in inventory investment with respect to changes in demand and price, i.e.

acceleration of stock level changes. Table 1.4 shows the negative equilibrium relationships between inventory investment and demand and price in the cointegrating vectors which are $i_{t-1} = -0.111y_t - 2.931\theta_t$ at high frequencies and $i_{t-1} = -0.093y_t - 3.725\theta_t - 3.341p_{t-1}$ at low frequencies for the pre-1973 period. The adjustment speed of inventory investment at high frequencies and low frequencies are -22.196 and -0.067 again confirming that the inventory investment will be reduced due to more stock being used to meet increasing demand when prices rise higher relative to its equilibrium. The results fit the inventory behaviors in the production smoothing motive in which stocks and inventory investment are both decreasing when prices go up regardless of time horizons.

Table 1.4: MLE estimates relationship of inventory investment, production, demand, and price

		Pre 1973		Post 1973	
		High Frequency	Business Cycle	High Frequency	Business Cycle
α	inv	-22.196***	-0.067***	-29.555***	-0.030***
		(1.773)	(0.009)	(2.342)	(0.007)
	production	-5.802**	-0.017	-1.076	-8.59e-6
		(2.056)	(0.012)	(1.305)	(4.36e-3)
	demand	0.012	8.301e-5	0.018***	-1.76e-5·
		(0.009)	(5.186e-5)	(0.003)	(9.44e-6)
	price	0.016*	1.634e-4**	0.0624**	-2.52e-4***
		(0.007)	(5.137e-5)	(0.019)	(6.34e-5)
β	inv	1	1	1	1
		(NA)	(NA)	(NA)	(NA)
	production	-0.111***	-0.093***	0.006	-0.005
		(0.027)	(0.020)	(0.029)	(0.069)
	demand	-2.931*	-3.725***	-17.111***	9.909
		(1.645)	(1.350)	(4.945)	(11.4416)
	price	-1.967	-3.341***	-1.741	9.480***
		(1.436)	(1.190)	(1.039)	(1.981)

'***' Indicates that the null hypothesis that the coefficient is equal to zero can be rejected at the 0.1% level, '**' the 1% level, '*' the 5% level, and '.' the 10% level.

On the other hand, the cointegrating vectors of stock level of the period from 1973-2013 also show the negative relationship with demand and price at both frequency ranges where $s_{t-1} = -97.298\theta_{t-1} - 49.108p_{t-1}$ for high frequencies and $s_{t-1} = -75.546p_{t-1}$ for low frequencies. It is clear that price is the only factor driving inventory investment in the long term since only its coefficient is significant in the low frequency cointegration vector. Both of the adjustment speed at high frequencies and low frequencies are -2.966 and -0.004 respectively indicating that when prices rise higher than the equlibrium level, stocks will decrease to restore the equilibrium. The cointegrating vectors of the inventory investment express the negative relationship with demand at high frequencies, $i_{t-1} = -17.111\theta_t$, and a positive relationship with price at low frequencies, $i_{t-1} = 10.562p_{t-1}$. This indicates that in the short term, inventory was drawn to buffer demand at an accelerating speed, but in long run, the drawn down speed of inventory wanes due to firms' ability to expand their capacities. Additionally, it provides an insight into how firms manage their inventories when their production is restricted. In the short run, the inventory investment responds only to changes in the demand since it is used to buffer demand shocks and avoid stockout. However, in the long run, firms' decisions to expand their capacities are based solely on the prospect of profits, hence the inventory investment simply responds to price changes. The results of the period 1973-2013 fit the behavior of inventories in the stockout avoidance motive described in the above models in which stocks decrease whenever demand and price rise while the inventory investment only decreases in the short-run but increases in the long-run due to the capabilities of firms to expand their productions.

The empirical results confirm the theories discussed in Section 3. During the flexible supply period, 1/1931-12/1972, oil inventory followed the production smoothing motive in which firms rely on inventory to manage demand shock. The evidences confirm that oil stock was drawn down when demand and price increase; and the draw down speed increases in the long run if demand and price continue to rise. Contrarily, oil inventory followed the stockout avoidance motive during the restricted production period from 1/1973 to 12/2012 when production is restricted. During this period, crude oil stocks can be seen to decrease in short term when demand and price increase. However, this stocks draw down speed is seen to slow down in long term when the inventory investment become positive. In the short term, when supply is inflexible, demand increases should reduce inventory stocks due to the firm's incapability of expanding production. In contrast, in the longer term, supply is more flexible, firms have time and resources to expand their production, and hence inventory investment will increase to provide a buffer against larger demand shocks. Nonetheless, the decision to expand capacities is based sole on the prospect of prices in the future.

Moreover, the volatility patterns of inventory at aggregate level also corroborate to the motive of holding inventory. It is shown in Table 1.5 on page 36 that inventory is less volatile than demand and output at all frequencies for the period before 1973. This confirmed that inventory was used to smooth production cost during the flexible production period. On the other hand, inventory investment is more volatile than demand and price at high frequencies but less volatile than demand and price at low frequencies. This affirmed that inventory took on the role of buffer to avoid stockout when production capacity was restricted.

Table 1.5: Volatility ratios

	Pre-1973		Post-1973	
	High Frequencies	Business Cycle	High Frequencies	Business Cycle
$r_{i/y}$	0.510	0.043	1.529	0.28
	(1.000)	(1.000)	(0.000)	(1.000)
$r_{i/\theta}$	1.179	0.005	4.150	0.422
	(0.043)	(1.000)	(0.000)	(1.000)

The first rows are the ratios of inventory to production or demand. p-values of the hypothesis that inventory is less volatile than production or demand respectively are in the parentheses on the second rows.

The inventory of crude oil at aggregate level has shown that it is used primarily as a buffer against the demand shocks. However, that does not mean that crude oil inventory has never been used as a speculation mean. To further investigate the possible speculation motive, the inventory at Cushing will be examined. Cushing is an important hub where WTI is delivered and NYMEX futures is priced. Thus, it could provide an intuitive understanding on how inventory decision is made. The cointegration tests confirmed that the inventory at Cushing, the price, and supply-demand factors are moving together.

Table 1.6: Cointegration tests of Cushing inventory

	Stock level		Inventory investment	
	High Frequency	Business Cycle	High Frequency	Business Cycle
$r <= 3$	1.71	14.24***	1.00	6.57*
$r <= 2$	17.18*	37.39***	3.27	38.78***
$r <= 1$	48.58***	95.52***	32.33**	151.78***
$r = 0$	110.53***	166.68***	146.38***	297.65***

'***' Indicates that the null hypothesis of no cointegration can be rejected at the 1% level, '**' the 5% level, '*' the 10% level.

The cointegration vectors of stocks at high frequencies is $s_t = 15.657\theta_t + 43.125p_t$ and at low frequencies is $s_t = 24.079y_t + 23.389\theta_t + 50.508p_t$. Both cointegrating vectors showed that inventory stocks and price are possitively correlated in their equilibrium relationships in the short-run and the long-run. The adjustment coefficients at high frequencies and low frequencies are -1.152 and -2.3e-4 and are both negative which imply that the stock levels will increase when prices rise above their equilibrium levels at all time horizons.

Table 1.7: MLE estimates relationship of stock level, production, demand, and price at Cushing

		stocks	production	demand	price
High frequencies	α	-1.152***	-0.043*	-0.044	-0.003
		(0.157)	(0.018)	(0.048)	(0.006)
	β	1.000	-2.584	15.657***	43.152***
		(NA)	(3.366)	(2.611)	(6.108)
Business cycle	α	-2.30e-4***	9.88e-6*	2.18e-5.	9.30e-7
		(3.09e-5)	(3.96e-6)	(1.21e-5)	(1.40e-6)
	β	1.000	24.079***	-23.389***	50.508***
		(NA)	(3.048)	(3.839)	(5.869)

'***' Indicates that the null hypothesis that the coefficient of the MLE estimate is equal to zero can be rejected at the 0.1% level, '**' the 1% level, '*' the 5% level, and '.' the 10% level.

The cointegration vectors of the inventory investment at high frequencies and at low frequencies are $i_t = -0.204y_t + 0.360\theta_t + 0.913p_t$ and $i_t = 0.359y_t + 0.135\theta_t + 0.721p_t$ respectively. The results also confirm that inventory investments and prices have positive equilibrium relationships in both of the short-run and the long-run. Both of the adjustment coefficients of the inventory investment are negative indicating that when prices deviate from their equilibrium levels, the inventory investments will adjust by moving in the same direction of price to restore the equilibrium.

Table 1.8: MLE estimates relationship of inventory investment, production, demand, and price at Cushing

		inv	production	demand	price
High frequencies	α	-29.634***	0.172	2.051*	-0.455***
		(2.965)	(0.354)	(0.938)	(0.126)
	β	1.00	-0.204·	0.360***	0.913***
		(NA)	(0.122)	(0.094)	(0.217)
Business cycle	α	-5.79e-3***	-4.73e-4***	-0.001***	-2.16e-6
		(5.46e-4)	(6.93e-5)	(0.000)	(2.50e-5)
	β	1.000	0.359***	0.135	0.721***
		(NA)	(0.089)	(0.113)	(0.114)

'***' Indicates that the null hypothesis that the coefficient of the MLE estimate is equal to zero can be rejected at the 0.1% level, '**' the 1% level, '*' the 5% level, and '.' the 10% level.

Did speculation drive the price?

The inventory movements at Cushing match the speculation motive. However, whether the inventory speculation distorts price as claimed by many other studies is a major concern. The problem for all of the models using regression or SVAR in previous studies is that all variables are regarded as endogenous and hence their values should be generated endogenously by the model and not be forced upon them exogenously. In reality, there could be cases where one or more of the variables are exogenous and not affected by feedback relations within the system under consideration. In such cases a conditional analysis as described in the preceding is plausible. Thus, exogeneity tests should be examined to determine the roles of other factors.

Table 1.9: Exogeneity tests for oil price

		High Frequencies			Business Cycle		
	H_0	Pre-73	Post-73	Cushing	Pre-73	Post-73	Cushing
Stock	$\alpha_4 = 0$	1.25	11.01	0.13	0.66	14.32	0.25
		(0.26)	(0.00)	(0.72)	(0.42)	(0.00)	(0.61)
Inv	$\alpha_4 = 0$	4.07	10.92	13.36	6.74	9.40	0.01
		(0.04)	(0.00)	(0.00)	(0.01)	(0.00)	(0.94)

This table reports the results of weakly exogeneity test of price. p-values are in the parentheses

The hypotheses that prices are weakly exogenous in equilibrium are not rejected at both high frequencies and business cycle frequencies for the Cushing stocks. Weak exogeneity is not rejected for the price at both frequency ranges implying that price is not affected by transitory perturbations of trading stock level. However, the exogeneity null hypothesis is rejected with the present of the inventory investment at high frequencies which implies that the acceleration in accumulating inventory does affect the market price in a very short term (weakly). In longer term, price seems not to be impacted by the inventory investment. By contrast, the weakly exogenous hypotheses of prices at the aggregate level are rejected at all frequencies for both pre- and post-1973 periods. This confirms that price is determined mainly by supply and demand rather than by speculative inventory through financial trading activities.

1.5 Conclusions

This paper presents an analytical framework to distinguish the roles of commodity inventory by looking into the behaviors of their relationships with prices, production and demands of oil at high frequencies (short-term) and business cycle frequencies (long-term). The distinct movements of inventories at high and low frequencies prove to be very useful in understanding the nature of inventory fluctuations and testing different hypotheses. Inventories provide a means to avoid stockout against demand uncertainty. Hence the safeguard stock level should decrease with the volatility of the market and marginal revenue.

When inventory is used to smooth production cost, inventory investment will decline at all frequencies since firms utilize inventory rather than expanding production to meet any unexpected demand shock. However, when inventory is used as a safety stock to avoid stock out, inventory investment should be negatively correlated with demand and price at high frequencies since supply is inflexible in the short-term. Whereas at low frequencies (long-term), production is more flexible, firms would invest in their capacity to avoid stockout. Thus inventory investment should expand with the increase in demand and price. On the other hand, speculation motive has shown that stocks and inventory investment would go up in response to the rise in price at all frequencies. The paper has provided evidence that stock level, or inventory investment, production, demand, and price are connected by stable relationships in both high and low frequencies. The empirical significance of cointegrating vectors that link stock, inventory investment with production, demand, and price variables suggest that the relationships are meaningful. This relationship is not merely a correlation but a causal relationship established by error correction vectors. Our finding confirms the role oil inventories at the aggregate level is to smooth production cost for the period from 1/1931 to 12/1972 and to buffers against demand shock for the studied duration from 1/1973 to 12/2012. While inventory investments respond to demand at high frequencies, it responds only to price at low frequencies for the restricted supply period. This implies that the decision to expand capacity and inventory is based on demand satisfaction in the short-run but depends on profit prospect in the long-run. This result reflects the reality that storage is expensive and limited, and oil is instead preferred to be kept underground, and the fact that oil producers often use price as a tool to adjust supply and demand. The inventory at delivery hub Cushing shows that futures trading inventory is used for financial speculation. However, this speculative inventory did not have destructive effects on price as claimed by other studies. Price of oil is determined supply and demand at the aggregate level.

Chapter 2

Pricing strategies and price discovery processes: A case of stainless steel

Full cost pricing is shown to connect the component costs to the product price. The surcharge system employed by stainless steel industry has linked nickel price, the major component cost, to the price of stainless steel. The reason that nickel but other components played a key role in determining the movement of stainless steel price was its volatility. Nickel futures market also helps guide the price discovery process and production planning of stainless steel. Nickel futures provide a tool to manage stainless steel risk since they are proved to be the accurate predictors of stainless steel prices under different loss functions compared to no-change forecast in most of our real-time data tests after accounting for shift in relationship of nickel and stainless steel over time.

2.1 Introduction

The pricing of goods and services plays an important role in the success of a firm. According to Marn and Rosiello (1992) a 1% price improvement could result in an 11.1% increase in operating profit, which compares to 1 percent improvements in variable cost, volume, and fixed cost only resulting in profit increases of 7.8%, 3.3%, and 2.3% respectively. There are a vast amount of studies in economics, marketing, and management revolving pricing strategies. Most of the literature studying pricing strategy have revolved around the pricing decision under demand uncertainty, see Leland (1972); Aiginger (1987); Fraser (1985); Fabiani et al. (2007), or the impact of pricing on the profitability of a firm, see Cannon and Morgan (1990); Ingenbleek et al. (2003). This paper explores a different angle of pricing strategy: the role of pricing in the price discovery process of composite commodities, especially in the case of stainless steel. Like other composite materials, stainless steel price depends not only the costs of its components but also the market fundamentals which make it hard to predict the price and to manage the price risk. Hence, findings in the case of stainless steel could have useful applications in the cases of other alloys and composite commodities.

Stainless steel is chosen to study because its industry has recently gone through changes in the way they price their products. Like many other commodities, stainless steel prices have been rising and falling wildly for the last several years. Steel producers have not only been exposed to the unprecedented volatility of stainless steel at a moment, but they also face the rising costs of raw materials over the years. The fluctuating costs and uncertain demands made marginal cost (market based) pricing difficult. To cope with constant changes in demand and price of stainless steel as well as the fluctuating costs of raw materials, the steel industry has decided to change their pricing practice by reintroducing a surcharge mechanism for nickel and adding chromium and magnesium to that list since the beginning of 2000s. The surcharge is an additional charge per unit weight that is added to the base price, and is calculated using the difference between the reference costs and the current element costs. The base price is estimated based on the cost of producing a specific alloy and is influenced by three factor: 1) supply-demand fundamentals, 2) cost factor for making a particular product such as the alloy content, the cost of making the particular form and size, and 3) a yield factor. Stainless steel consumers are offered the base price when they place an order, then the surcharge will apply at the time of shipment. Other reasons that stainless steel deserves our attention are its broad applications and the size of its market. Stainless steel has wide applications in various end-use industries including construction, transportation, industrial machinery, household appliances, metal goods, and electronics owing to its inherent characteristics such as durability, high tensile strength, and resistance. The underlying asset value of the global steel industry is enormous with the estimated value of about $420bn compared to $162bn of base metals and is on a growing trend[1].

The goal of this paper is to determine whether the cost of components pass through the supply chain and reflect in the price of stainless steel under different pricing strategies; and how these findings could help manage risks associated with price fluctuation. To this end, it is necessary to examine the formations of stainless steel price under each pricing strategy. It was shown that under market based pricing, the product price was not only depended on the component costs but was also determined largely by the supply-demand factor baked into the profit. The profit required by a firm under market based often large to offset the fluctuation in production costs during the lead time. On the other hand, the material price risk was passed on consumers entirely under full cost pricing. In this case, firms bear minimum or no risk, hence their desired profits are usually small and stable for a long period of time. This can be observed in the base price of stainless steel which is much smaller than the total cost and is kept unchanged for a long period of time. While costs determine the price level of the product, the component volatility are the main force driving the movement of product price. We know that volatility determines the movement of price. A product volatility is determined by the volatility of each component and their covariances.

To look at how price is formed, historical decomposition will be performed to determine how much each component price shock contributes to the stainless steel price before and after surcharges were applied. The components contribute to the price of stainless steel are the cost of major components such as nickel, chromium, iron, energy cost, and supply–demand factors. Nickel price shock was found to play a major role in explaining

[1] "Trade statistics for international business development". Trade Map 2014, via http://www.trademap.org/Index.aspx

stainless steel price since surcharges were reintroduced in 2000. Behind nickel, chromium price shock is the second factor in constituting stainless steel price from time to time. Other shocks are either minute or their effects are not in the same direction as steel price movements. As mention previously, the volatility of stainless steel was determined by the combination of all component's volatility. Since nickel is the most volatile among the component, it plays a key part in driving stainless steel price.

Understanding price formation is important since it affects the expectation of the price and consumption/production of stainless steel in the future. Nickel contributes largely to the price movements of stainless steel, any expectation of nickel future spot price should impact the price of the stainless steel as well. Nickel futures has been proven to efficiently reflect the price of nickel in the future. For that reason, nickel could used as referenced cost to plan for production and consumption of stainless steel. In fact, nickel futures rates were shown to be efficient predictors for stainless steel at any time horizons longer than 1 month. Moreover, the nickel production which was driven by the future price expectation was also shown to drive the stainless steel production after the surcharge was applied.

The accuracy of nickel futures in predicting future spot price of stainless steel plays an important role in managing price risk. Hence, the forecastability of nickel was put into tests since an efficient forecaster would not mean to be a accurate predictor. Multiple real-time out-of-sample forecast models using nickel futures contracts were analyzed under different loss functions and time horizons. Nickel futures was found to be the accurate predictor under symmetric loss function but asymmetric loss functions. This non-rejection bias was due to the fact that the loss functions of the evaluation and the econometric method (least squared regression) were the same. However, nickel futures was consider to be the most accurate predictor of stainless steel when the shift between nickel and stainless steel prices over time was accounted.

The paper is structured as followed. In section 2, I will provide some stylized facts about stainless steel to explain the rationale behind price series chosen to study in this paper. Section 3 studies the price formation of stainless steel under different pricing strategies. The historical decomposition method was used to analyzed the links between steel price and the component costs. Section 4 will study the impact of nickel price expectation on the price and the production of stainless steel . Finally, section 5 presents some concluding remarks along with points for future research.

2.2 Stylized facts about stainless steels

Stainless steel, also known as inox, is a generic name for a wide range of types and grades of steel alloys that have a corrosion resistant property. Stainless steels are iron alloys with a minimum of 10.5 percent of chromium. Other elements such as nickel, molybdenum, titanium, copper, carbon, and nitrogen are added to enhance stainless steel's structure and properties such as formability, strength, and cryogenic toughness. Nickel changes the crystal structure of stainless steel from body-centered cubic (ferric) to face-centered cubic (austenic). Approximately 85 percent of nickel was used in alloys such as stainless steel and super alloys[2]. Hence, stainless steels are sometimes classified by their crystalline structures.

Types and grades of stainless steels are designated based on the corrosion resistant requirements.

- Austenitic stainless steels which include 200 and 300 series have an austenitic crystalline structure. Austenite steels contain at most 0.15 percent of carbon, at least 16 percent chromium, and sufficient amounts of nickel and/or manganese. They make up over 70 percent of total stainless steel production. The grade 304 which is also known as 18/8 for its composition of 18 percent chromium and 8 percent nickel is the most widely used austenite steel. The second most commonly used austenite steel is the 316 grade which is known as 18/10 for its typical composition of 18 percent chrome and 10 percent nickel.

- Ferritic and martensitic stainless steels together make up the 400 series. Ferritic stainless steels generally have better engineering properties than austenitic stainless steel. However, their resistance to corrosion property is reduced because of lower chromium and nickel content. Martensitic stainless steels are less corrosion resistant compared to the other two classes of stainless steel, but they are extremely strong and

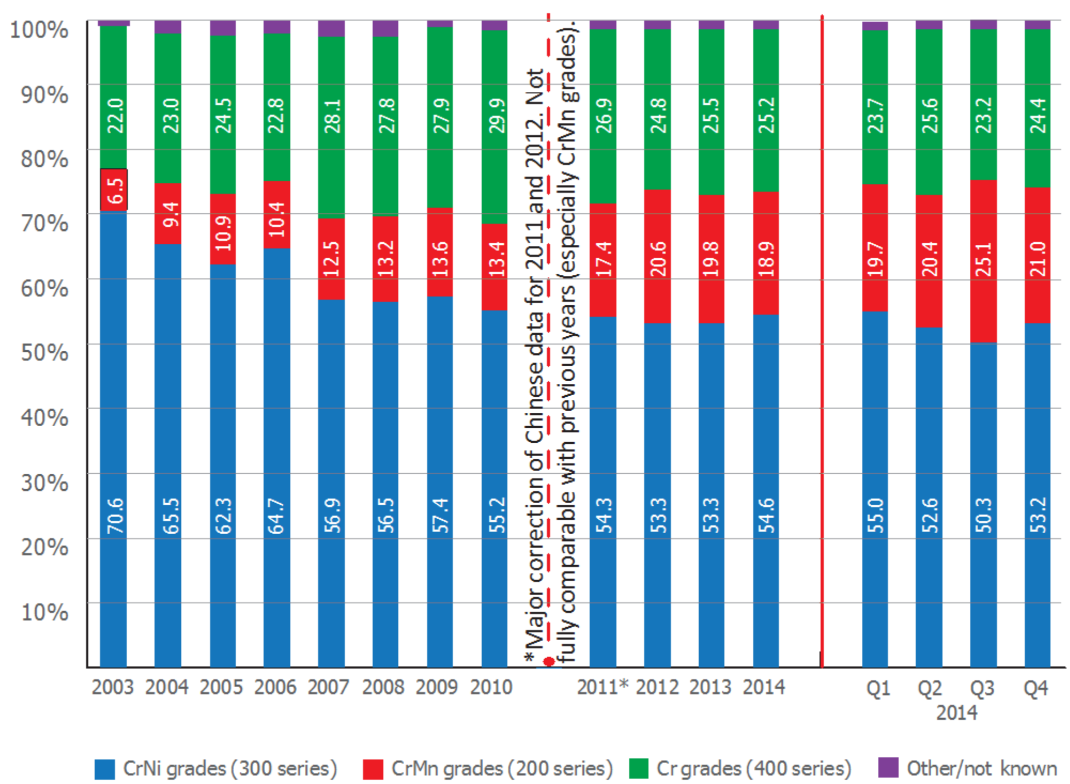
[2] "Nickel Metal - The Facts." Nickel Institute, http://www.nickelinstitute.org/NickelUseInSociety/AboutNickel/NickelMetalt

tough. Martensitic stainless steels contain 12-14 percent chromium, 0.2-1 percent molybdenum, less than 2 percent nickel, and about 0.1-1 percent carbon.

- Duplex stainless steels have a mixed property of austenite and ferrite. They are characterized by 19-32 percent of chromium, up to 5 percent of molybdenum, and a lower amount of nickel compared to austenitic stainless steels. Duplex stainless steel, first produced in 1930, have roughly twice the strength of austenitic stainless steels but are less expensive than many austenitic grades since they contain less nickel.

Total stainless steel production in the western world has grown at about 4.8 percent per year since 1950. Since 2007, the austenitic share of global stainless steel accounts for between 71 percent and 75 percent of total stainless steel output, the rest is ferritic or martensitic. The production of each grade is shown in figure 2.1.

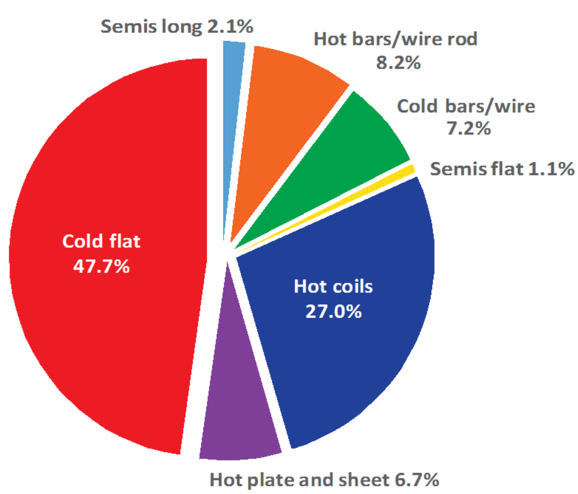
Figure 2.1: Stainless Melt Shop Production by Grade: 2002 - 2013



The data are from Stainless Steel In Figures 2015, International Stainless Steel Forum

Each grade can be produced in several different forms. Steel products can be divided into flat and long products from a geometrical point of view, or by an alternative way of following the production route, starting with semi-finished products, rolled products, and products finished with additional operations. Flat steel products consist of plates and hot or cold rolled coils or sheets. These products are used in a wide range of industries such as automobile, domestic appliances, shipbuilding, and construction. Long products include a variety of forms such as rods, bars, wires, rails, tubes, and sections. Many of the products originate from hot-rolled rod coil that is further processed. The percentage of stainless steel products traded worldwide is shown in figure 2.2.

Figure 2.2: Stainless Steel Foreign Trade in 2014



We will use the price of stainless steel 304 cold rolled coil in this study since series 300, particularly, grade 304, is the most common stainless steel grade and the flat cold rolled products are the most traded. In addition, grade 304 is also a standard price that is followed by industries. In the following section, we will use historical decomposition to dissect the effects of component metal price shocks and other cost shocks on the stainless steel price. We will find that energy cost does not play any significant role in determining the movement of stainless steel; hence, production methods of different types of stainless steels would have no effects on the price movements.

2.3 Formation of stainless steel price

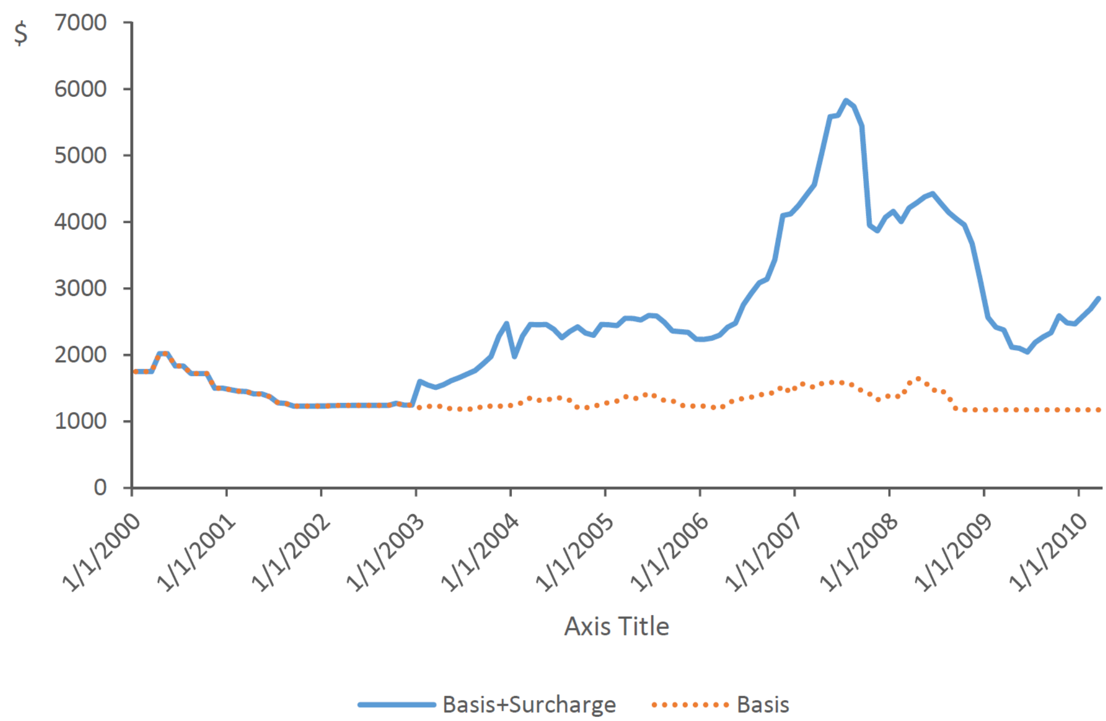
The product unit cost can be written as, $C = c_0 + \sum_{i=1}^{n} k_i C_i$, where c_0 is a known base cost such as labor cost and the referenced price, C_i is the price shock of component i, and k_i is the percentage of weight of component i. The unit cost of stainless steel is influenced greatly by the component commodity prices which can be very volatile during the production lead-time. The producer bears the risk of commodity price shocks during the production lead-time.

Under the market based pricing, the producer will charge the buyer an amount, $W = E[C] + \pi$, which equals the expected cost plus some profit. This profit is depend on the supply-demand factor of the market and should be large enough to cover any difference between the estimated cost and the actual cost. Hence, the selling price can be written as $W = C + \varepsilon + \pi$, where $\varepsilon = E[C] - C$ is the error of the cost estimates. The more volatile the component, the larger the error, consequently leads to lesser pass-through and weaker contribution of costs to the product price. Moreover, the product price under market based pricing will not only depend on the component metal prices but also depend on the supply and demand that drive the profit factor.

Under cost plus method, the producer will charge a base price and the surcharge to cover the unexpected cost shocks, $W = \omega + \sum_{i=1}^{n} k_i C_i$. The base price includes reference costs of components and a desired profit, where $\omega = c_0 + \pi$. The profit here is often smaller and stable since the buyer bears all the risk. The referenced costs are also kept unchanged for a long period of time (see figure 2.3). Hence, the product price will depend solely on the component prices.

The changes in product price depend on the products volatility. Under market based pricing, the volatility of the product price is contributed by not only the volatility of the component costs but also by the market volatility and the supply-demand factor driving the

Figure 2.3: Stainless steel 304 base price and surcharge



profit, $\mathrm{Var}(W) = \mathrm{Var}(C) + \mathrm{Var}(\varepsilon) + \mathrm{Var}(\pi) + \mathrm{Cov}(C,\varepsilon) + \mathrm{Cov}(C,\pi) + \mathrm{Cov}(\varepsilon,\pi)$. On the other hand, the product price volatility under full cost pricing is driven mainly by its component volatility since the profit is almost constant, $\mathrm{Var}(W) = \mathrm{Var}(C) = \sum_{i=1}^{n} k_i^2 \mathrm{Var}(C_i) + \sum_{i \neq j} k_i k_j \mathrm{Cov}\left(C_i, C_j\right)$. Thus, the component with higher volatility and weight percentage will dominate the movement of stainless steel price.

The price of stainless steel depends on the production costs and market's supply-demand. As we discussed in the previous section, the main elements used in making stainless steel are iron, nickel, and chromium. Besides that, energy costs contribute significantly to the total cost of production. Steel production is an intensive energy consuming process. It takes the equivalent of 2.07 barrels of oil to produce a ton of steel. Energy cost accounts for approximately 20% of the total cost. About 50% of an integrated facility's energy input comes from coal, 35% from electricity, 5% from natural gas and 5% from other gasses.[3] The breakdown cost per component of stainless steel and their percentage of stainless steel prices as on December 31, 2014.

Table 2.1: Breakdown of stainless steel cost

	Weight (%)	Price ($)	Percentage of Price
Stainless steel	100	3053.40	100%
Chromium	18	444.45	14.55%
Nickel	8	1205.92	39.49%
Manganese	2	44.72	1.46%
Iron	72	48.96	1.60%
Energy	NA	549.61	17.99%

It is easily seen that nickel, chromium, and energy are the dominant cost components of stainless steel. While the price level depends on the total component costs, the price movement is driven mainly by the component volatility. Nickel volatility is significantly larger than those of other component commodities (see Table 2.2). The volatility of nickel also grew larger after 2000. Thus, we could expect to see the larger contribution of nickel price on the movement of stainless steel price.

As discussed above, a surcharge pricing system which was reintroduced by steel producers since the beginning of the year 2000, would certainly affect how cost of component metals were transferred into the stainless steel price. To study the possible effect of the surcharge on the price of stainless steel, the ex- and post-2000 period will be examined. There are several methods that could be used to measure price transmission including the ratio of percentage changes between two time periods, correlation coefficients, regression analysis, co-integration analysis. However, those aforementioned methods are only suitable for the bivariate and static analysis. To address the need of multivariate analysis of the shocks, and the dynamic in the price and component costs, a historical decomposition method will

[3] Fact sheet: Energy use in the steel industry, Worldsteel Association, 2016. https://www.worldsteel.org/publications/fact-sheets/content/02/text_files/file0/document/fact_energy_2016.pdf

Table 2.2: Covariance matrix between component prices

(a) Before 2000

	Nickel	Chromium	Iron	Coal
Nickel	2003310			
Chromium	205826	76177		
Iron	729	31	6	
Coal	499	795	6	24

(b) After 2000

	Nickel	Chromium	Iron	Coal
Nickel	76004506			
Chromium	4554072	132513		
Iron	269178	47538	2804	
Coal	137004	32550	1650	1168

be used to analyze the effects of price shocks from multiple components on stainless steel prices.

2.3.1 Historical decomposition

To look at the contribution of the structural shocks to the stainless steel price, a historical decomposition method proposed by Burbidge and Harrison (1985) was used. The historical decomposition framework is often used to identify shocks as well as their magnitude and directions of effects on the data. Beidas-Strom and Pescatori (2014) used historical decomposition to analyze the effect of supply, demand, and speculation shocks on the price of crude oil. Bian and Gete (2014) employed the same technique to show how population, credit, and productivity contributed differently to China house prices before and after 2009. Ferrucci et al. (2012) decomposed food prices to study whether consumer price shock, producer price shock, and commodity price shock contributed to the rising food prices.

Historical decomposition is based on the vector autoregressive (VAR) model and its moving average (MA) representation. Consider a structural VAR model for a vector y_t containing m variables:

$$y_t = c + \sum_{j=1}^{p} A_j y_{t-j} + \varepsilon_t \tag{2.1}$$

Neglecting the deterministic term, the close form MA representation of VAR model can be written as follows

$$y_t = A(L)^{-1}\varepsilon_t = \Phi(L)\varepsilon_t = \sum_{j=0}^{\infty} \Psi_j \varepsilon_{t-j} \tag{2.2}$$

The i^{th}variable can be represented as

$$y_{it} = \sum_{j=0}^{\infty} \left(\psi_{i1,j}\varepsilon_{1,t-j} + \ldots + \psi_{ik,j}\varepsilon_{k,t-j}\right) \tag{2.3}$$

where $\psi_{ik,j}$ is the $(i,k)th$ element of the structural MA matrix Ψ_j. Each component $\psi_{ik,j}\varepsilon_{k,j}$ shows what the history of $y_{i,t}$ would have been if the k-th shock had been the only one affecting the system. Thus,

$$y_{it}^{(k)} = \sum_{j=0}^{\infty} \psi_{ik,j}\varepsilon_{k,t-j} \tag{2.4}$$

is the contribution of k-th structural shock to the i-th variable $y_{i,t}$. Historical value can be partitioned into accumulated effects of current and past shocks, and a base projection.

$$y_{it}^{(k)} = \sum_{j=0}^{t-1} \psi_{ik,j}\varepsilon_{k,t-j} + \sum_{j=t}^{\infty} \psi_{ik,j}\varepsilon_{k,t-j} \tag{2.5}$$

The first sum is the contributions of innovation k-th to variable i-th. The second sum is the dynamic forecast of y_t conditional on the past information. We can estimate the second part of the sum recursively by successive substitution the VAR process in (1)

$$y_{it}^{(k)} = \sum_{j=0}^{t-1} \psi_{ik,j}\varepsilon_{k,t-j} + \alpha_{i1}^{(k)} y_0 + \ldots + \alpha_{ip}^{(k)} y_{-p+1} \tag{2.6}$$

The series $y_{it}^{(k)}$ represents the contributions of k-th structural shock to the i-th component series of y_t, given $y_0, \ldots, y_{-p+1}$. The corresponding series $y_{it}^{(k)}$, $k = 1, \ldots, K$, is a historical decomposition of y_{it}, and $a_{ij}^{(k)}$is the i-th row of $A_j^{(t)}$. For stationary VARs, $A_j^{(t)}$ go to zero when t becomes large so that the contribution of the initial state becomes negligible for stationary process as $t \to \infty$. On the other hand, for $I(1)$ processes, the contribution of the initial values $y_0, \dots, y_{-p+1}$ will remain important.

2.3.2 Data

Data used in this study was divided into two periods. The first period starts from January 1991 to its end in December 1999, when stainless steel was priced on basis only. The second period, when surcharges were applied on top of the basis of stainless steel price, covers a period from January 2000 to December 2014. All the data series used in this study are monthly data. The nickel price was the cash price or the settlement price on the London Metal Exchange. Coal price was used as a proxy for the energy price since coal accounts for more than 50 percent of energy input, and more than 33% of the electricity generated in the United States in 2015 was from coal[4]. The chosen coal price, which can be obtained from World Bank commodity data, was Australian thermal coal, 12,000- BTU/pound, less than 1% sulfur, and 14% ash, FOB price at Port Kembla, Newcastle. The price of West Texas Intermediate crude oil, and the price of Henry Hub natural gas were alternatively used as a proxy for energy price but produced no difference in the estimates. Hence, the results below presented the estimates with coal price. The chromium series is ferrochrome price in Pittsburgh warehouse with 6-8% Carbon, 60-65% Chromium, and maximum 2% Silicon. The studied stainless steel price was the domestic price of cold rolled coil (sheet) grade 304 2mm ex-mill U.S. production. The stainless steel price was made up from two series. The stainless steel series in the first period, starting from January 1991 and ending in December 1999, is from Purchasing Magazine and could be obtained from Bloomberg terminal. The stainless steel series for the second period when surcharges were applied, starting from January 2000 and ending in December 2014, is from two sources. The first part of this series, from January 2000 to June 2007, is from Purchasing Magazine and is available on Bloomberg terminal. The second part of the series is from July 2007 to December 2014 and is acquired from Platts.

[4]https://www.eia.gov/tools/faqs/faq.cfm?id=427&t=3

Since there were large differences in prices of metals and energy, the data were standardized by dividing each series by its own standard deviation to avoid scaling problems in the calculation. Data was also tested for the unit root since the series that are more likely to reject unit root tests may also be those with less persistent shocks. The results of unit root and nonstationary tests are presented in the table 2.3.

Table 2.3: Unit root tests

	Level data		Differenced data	
	ADF	PP	ADF	PP
Nickel	-1.7658	-0.6118	-11.0092***	-10.9931***
Chromium	-1.5506	-0.2601	-10.9815***	-10.9564***
Iron	-1.4562	-0.4869	-8.9133***	-8.9345***
Coal	-1.6096	-0.3605	-10.0586***	-10.0663***
Stainless steel	-1.3789	-0.0617	-9.9262***	-9.9081***

‘*** indicates that the null hypothesis of unit root or nonstationary can be rejected at the 1% level, ‘** the 5% level, ‘* the 10% level.

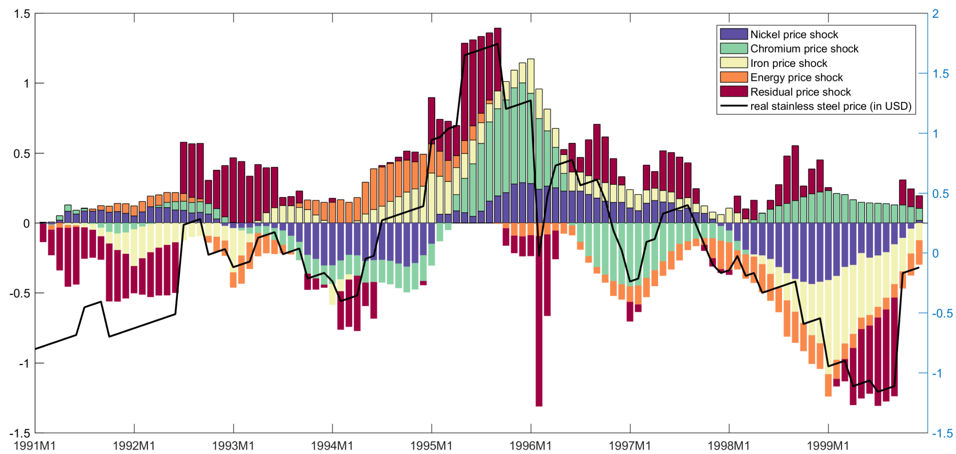
Two standard tests were selected to evaluate the stationarity of the data, the Augmented Dickey Fuller (ADF) test and the Phillip-Perron (PP) test. Test statistics confirm that all the price series are $I(1)$, or differenced stationary.

2.3.3 Historical decomposition of stainless steel price

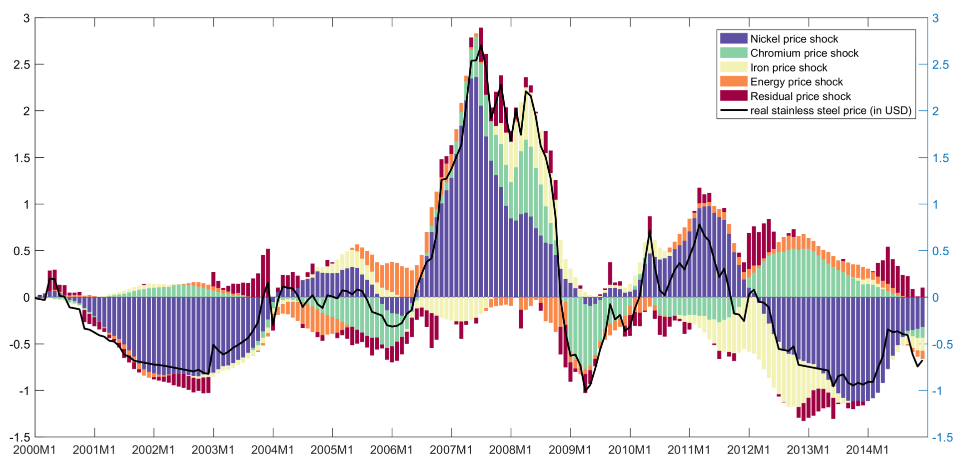
The contributions of each component metal price shock and energy price shock to stainless steel price were computed and presented in the following graph.

Figure 2.4: Historical decomposition of stainless steel price

(a) Pre-2000



(b) Post-2000



The historical decomposition plot shows the cumulative effects at each point in time of the price shocks of nickel, chromium, iron, energy, as well as the residual price shock which is the shock describing the movements of stainless steel that could not be explained by those component price fluctuations. figure 2.4 shows how the real stainless steel price would have evolved if the structural shock in question was present. A bar that is increasing over time means that the shock of which the bar is representing is exerting an upward pressure on the stainless steel price, and vice versa. The height of the bar represents the magnitude of the shock. figure 2.4a shows that none of the component metals nor energy price were able to explain the movement of stainless steel price adequately before 2000. The residual price shock played a critical role in every important change of stainless steel price. This confirms that supply and demand, not the cost of energy nor the component metals, were the key factors in determining the price of stainless steel under market based pricing. On the other hand, when surcharges were applied, nickel price shock was dominating across the sample after 2000 (see figure 2.4b). Besides that, chromium price shock played a significant role from time to time, especially during the brief rebound of stainless steel price in mid-2008, and the further drop in early 2009. Other price shocks were either not significant, nor were capable to explain the movement of stainless steel. This implies that different steel grades or different producing methods will not influence the price movements. Different stainless steel grades and products that contain various amounts of nickel will have differences in price levels by some constants, but their direction of price movements will be determined by the movement of nickel price. The minute effect of residual price shock confirmed the assumption that most stainless steel demand pressure is passed through the supply chain and is absorbed into the prices of component metals, especially nickel.

2.4 Stainless steel's price and production expectation

The difference between nickel and other components is that nickel has a very active futures market. If nickel futures fully reflects the expectation of nickel spot price in the future, then nickel futures contracts will provide insight on the direction of stainless steel price. For that reason, nickel futures market would help guide the price discovery process of not only nickel but also of stainless steel. Price expectation also dictates production choices. Hence, we could see the production of nickel affects the production of stainless steel as well. Therefore, in this section, the ability of nickel to influence the price and the production of stainless steel will be examined.

2.4.1 Price expectation

Commodity asset prices in the financial market, specifically stainless steel in this case, should reflect all available information; as consequence, prices should be consistent with the fundamentals such as costs, supply and demand factors. When the cost of stainless steel is expected to rise, the price of stainless steel will increase in the futures. As shown in the previous section, nickel contributes a large portion to the cost of stainless steel and plays a major role in changes in stainless price. Therefore, if nickel futures contracts fully reflect the future prices of nickel, then it should disclose the information regarding changes in stainless steel price as well. Hence, the efficient market hypothesis is almost certainly the right place to start when thinking about asset price formation and expectation.

The theory of rational expectations assumes that the outcomes of many economic situation depend partly on what people expect to happen. Moreover, the concept of rational expectations asserts that outcomes do not differ systematically (i.e. regularly or predictably) from what people expect them to be. In other words, it does not deny that people often make forecasting errors, but it does suggest that errors will not persistently occur on one side or the other.

$$S_{t+n} = E_t\left(S_{t+n}\right) + \varepsilon_t \tag{2.7}$$

where ε_t is the rational expectations realized forecast error, and must have conditional expected value of zero and be uncorrelated with any information available at time *t-n*.

Also, under the notations of risk neutrality and rational expectation, the concept of unbiasedness suggests that the current futures price, $F_{t,n}$, of the contract written at time *t-n* and expiring at a specific time *t*, should equal the spot price expected to prevail at time *t*.

$$F_{t,n} = E_t\left(S_{t+n}\right) \tag{2.8}$$

However, futures price $F_{t,n}$ observed at time *t* for the price of an underlying asset at time *t+n* is not always equal futures spot price but rather reflects future variation of future spot rate S_t (Fama, 1984). Thus, futures rate can be divided into an expected future spot rate $\left(E_t\left(S_{t+n}\right)\right)$ and risk premium $\left(P_t\right)$.

$$F_{t,n} = E_t\left(S_{t+n}\right) + P_t \tag{2.9}$$

Then equation (2.7) can be written as

$$S_{t+n} = \alpha + \beta F_{t,n} + \varepsilon_t \tag{2.10}$$

Which is, the expected future spot price, S_{t+n}, equals the current futures price of an asset, $F_{t,n}$, plus some constant risk premium α, where $\alpha = P_t$, at time t.

This unbiasedness hypothesis can also be interpreted as the simple efficiency hypothesis proposed by Hansen and Hodrick (1980) and the speculative efficiency hypothesis proposed by Bilson (1981), since the test for unbiasedness implies that forward rate tend to equal the market's expected future spot price or all relevant information is used by the market in determining the forward rate as a predictor of future spot price or there are no observable factor which would be helpful in making prediction. As such, the hypothesis that futures prices are unbiased predictors of spot prices is a joint hypothesis that market is efficient and that risk premium is not present. Therefore, a joint test for possible bias in forward rate and market efficiency can be estimated based on the regression of the difference in future spot rate on the current forward premium.

$$S_{t+n} - S_t = \alpha + \beta\left(F_{t,n} - S_t\right) + \varepsilon_t \tag{2.11}$$

Unbiasedness implies that the current futures price is indeed the best forecaster of the expected future spot price and that the current futures price should incorporate all available information. In other words, the implication of unbiasedness is that traders can be assured that in general, over time (or in long run), the current futures price is likely to predict accurately future spot rates without the trader having to pay a risk premium for the privilege of trading the contract. Hence the futures price is a long-run unbiased and efficient predictor of spot price when the joint restriction of $\alpha = 0$ and $\beta = 1$ is satisfied.

There are a significant number of studies examining the efficiency of futures rates in predicting commodity prices. Goss (1981) studied the unbiased predictor's properties for the spot prices of copper, tin, lead, and zinc in London Metal Exchange during the period of 1971-1978. Sephton and Cochrane (1991) also examine the unbiasedness hypothesis in the LME market with respect to six metals over the period 1976-1985. Bigman et al. (1983) studied the predictive power of commodity futures price for wheat, soybean, and corn. Chernenko et al. (2004) applied standard efficiency tests for wide ranges of forward rates including those of foreign exchange rates, interest rate, oil, and natural gas. Another framework that was often used to test the biasedness hypothesis was cointegration. Watkins and McAleer (2006) used cointegration framework to analyze the risk premium hypothesis using three-month futures contracts of aluminum, aluminum alloy, copper, lead, nickel, tin and zinc for the period of 1986 to 1998. Also using cointegration framework, Switzer and El-Khoury (2006) investigated the efficiency of the New York Mercantile Exchange (NYMEX) Division light sweet crude oil contract market during recent periods of extreme conditional volatility. Haigh (2000) investigated the relationship between freight cash and futures price using cointegration econometric.

The commonality among these studies regardless of the analyzing technique is that they all use futures contract of the same underlying commodities as predictors for future spot prices of those commodities. In the case of stainless steel, there is no existing futures market. However, in the previous section, it was shown that nickel played an important role in determining the movement of stainless steel price. Hence, an attempt will be made to use nickel futures contracts as predictors for future spot prices of stainless steel prices and then proceed to investigate the unbiased and efficiency hypothesis. On average, nickel price is 6 times higher than stainless steel, then equation (2.8) can be expressed as follows

$$S_{t+n} = \frac{1}{6} F_{t,n}^{Ni} \tag{2.12}$$

Also, nickel cost accounts for around 50 percent of stainless steel price. Thus, one percent increases in nickel price will expect to lead to about 50% increases in stainless steel. That is

$$\ln\left(\frac{S_{t+n}}{S_t}\right) = 0.5 \ln\left(\frac{1/6 F_{t,n}^{Ni}}{S_t}\right)$$

or

$$\ln\left(\frac{S_{t+n}}{S_t}\right) = -0.89 + 0.5 \ln\left(\frac{F_{t,n}^{Ni}}{S_t}\right) \tag{2.13}$$

The amount -0.89 in equation (2.13) is the risk of cross predicting using nickel futures, and the amount 0.5 is due to the account of the cost of nickel with respect to stainless steel price. Those are unavoidable risks associated with using cross predictor. However, they are not systematic errors, or any premium pays to speculators to provide insurance for price risk as mentioned above. Without loss of general, those amounts associated with cross predicting can be ignored, and the joint test for bias and efficiency predictor can be shown as

$$\ln\left(\frac{S_{t+n}}{S_t}\right) = -0.89 + \alpha + 0.5\beta \ln\left(\frac{F_{t,n}^{Ni}}{S_t}\right) \tag{2.14}$$

Consider the full-sample regression model

$$\Delta \ln(S_{t+n}) = \alpha' + \beta' \left(\ln\left(F_{t,n}^{Ni}\right) - \ln(S_t)\right) + \varepsilon_{t+n},\ n = 1,3,6,9,12 \tag{2.15}$$

where $\alpha' = -0.89 + \alpha$, and $\beta' = 0.5\beta$

Then nickel futures rates are unbiased and efficient predictors of stainless steel price if the joint condition $\alpha = 0$, and $\beta = 1$ is satisfied. In the other words, $\alpha' = -0.89$ and $\beta' = 0.5$ must hold jointly in order for nickel futures to be unbiased and efficient predictors for stainless steel. The test results are shown in table 2.4 below. The table shows coefficient estimates of α and β in equation (2.15) along with their associated p-values in F-tests of hypotheses that $\alpha = 0$, and $\beta = 1$, and Wald test of joint restriction of $\alpha = 0$ and $\beta = 1$.

Table 2.4: Asymptotic p-value for forecast efficiency

Horizon	$\hat{\alpha}'$	$\hat{\beta}'$	$H_0: \alpha' = -0.89$	$H_0: \beta' = 0.5$	$H_0: \alpha' = -0.89, \beta' = 0.5$
1-month	-0.291	0.168	0.000	0.000	0.000
3-month	-0.704	0.408	0.095	0.118	0.165
6-month	-1.010	0.592	0.340	0.281	0.144
9-month	-1.123	0.669	0.246	0.190	0.187
12-month	-1.113	0.673	0.251	0.186	0.256

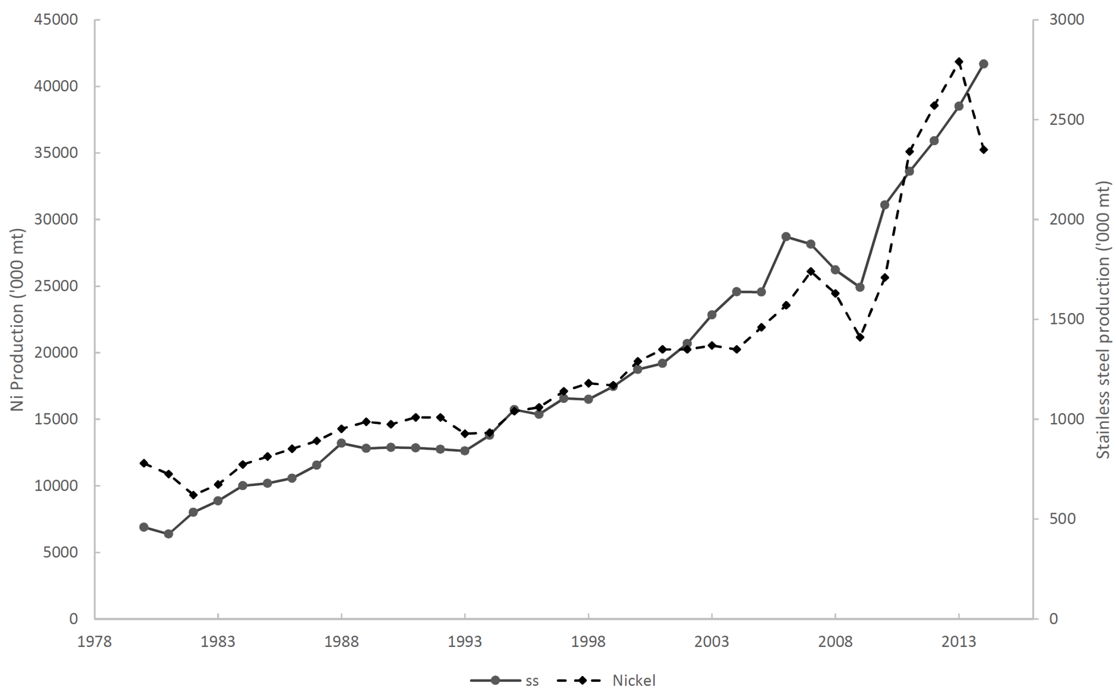
This table reports the estimates of α' and β' of equation (2.15), and the null hypothesis testing of $\alpha' = 0$, $\beta' = 0$, and $\alpha' = 0$, $\beta' = 0$ respectively.

The results confirmed that nickel price expectation was a crucial determinant of stainless steel price. The hypothesis of forecast efficiency at one-month horizon is rejected but is not rejected at any longer horizons (see table 2.4). Inventory could be the factor that explains the rejection of nickel futures rate as an efficient predictor of stainless steel at one month horizon. Companies hold inventories for both raw material and final products to facilitate productions and buffer against any unpredictable surge in demand. When nickel price goes up, steel producers will draw nickel from storage for manufacturing activities. Also, a stainless steel inventory could help a producer to satisfy demands before producing new products that would utilize higher priced nickel. Inventory help smooth the price fluctuation in the face of shifting supply and demand. Therefore, nickel price will not affect stainless steel price in the short-term until old inventories were replaced by the newer ones that are produced with the new price nickel.

2.4.2 Production expectation

Price expectation strongly determines production choices (Ezekiel, 1938). If the production cost is expected to increase, producers might want to advance their production schedule and maintain inventory to take the advantage of lower cost. On the other side, consumers also want to place other in advance to avoid the rise in price. Higher nickel price implies higher production. Since nickel was a key cost component of stainless steel, and rising nickel price was shown to push up stainless steel price in the last section, producers (consumers) of stainless steel would want to produce (buy) in advance to avoid higher cost (price). Therefore, nickel production is expected to affect the production of stainless steel. The figure 2.5 shows that nickel production seems to slow down compared to stainless steel production starting from 2002. Hence, the first step is to determine the possible break in the relationship between the productions of nickel and stainless steel.

Figure 2.5: Nickel-Stainless steel production



The rolling Chow test was used to identify the earliest possible structural break

$$Ni_t = \alpha + D_t + \gamma TR_t + SS_t + \varepsilon_t$$

where D_t is the dummy variable for the break point, and TR_t is the trend. The test found a statistical significant break in 2002. Furthermore, to study how the production of nickel and stainless steel has changed during these periods, causality test was performed to measure the influence of nickel and stainless steel production onto each other. Since the production series are nonstationary, Toda and Yamamoto (1995) non-Granger causality test was used to overcome this issue. The results of the bivariate Toda-Yamamoto augmented non-Granger causality tests in table 2.5 confirms that production of nickel indeed drove the production of stainless steel after surcharges were applied.

Table 2.5: Causality tests for Nickel-Stainless Steel production

SS production	to Ni production	from Ni production
Before 2002	13.310	2.858
	(0.000)	(0.091)
After 2002	2.482	46.226
	(0.477)	(0.000)

This table reports the Toda-Yamamoto non-causality tests between nickel and stainless steel production. The *p*-values are in the parentheses.

2.5 Nickel as an accurate predictor of stainless steel

If nickel futures could indeed predict stainless steel price efficiently and accurately, it would not only provide tools to manage price risk such as forecasting and hedging stainless steel price risk, but also have applications in creating financial instruments that allow investors to diversify their portfolio such as index and ETF. However, market efficiency theory implies that prices reflect all available information, but it does not imply certain knowledge. Many pieces of information that are available and reflected in prices are fairly uncertain. The efficiency of markets does not eliminate that uncertainty and therefore does not imply perfect forecasting ability. Chiang (1998) found that satisfying the efficiency hypothesis did not guarantee the out-of-sample forecasting power of forward exchange rate of the variety of currencies from January 1974 to August 1983. Bossaert and Hillion (1999) investigated monthly stock returns in several international stock markets. They found that the in-sample predictability broke down in out–of-sample forecast sometime around 1990. In this section, to measure the performance of the nickel as a predictor for stainless steel price, the rolling regression is applied to generate out-of-sample forecasts and their errors will be compared with random walk model.

The Benchmark model

If there is no available information that could help forecast the future spot price, and changes in the spot price are unpredictable, then the best forecast of the future spot price of stainless steel is simply its current spot price. Hence, a natural benchmark for forecasts based on the price of nickel futures is provided by the random walk model without drift.

$$\hat{S}_{t+n|t} = S_t, \qquad n = 1, 3, 6, 9, 12 \tag{2.16}$$

Given that stainless steel prices have been persistently trending upwards (or downwards) at times, it is natural to consider a random walk model with drift. One possibility is to estimate this drift recursively, resulting in the forecasting model

$$\hat{S}_{t+n|t} = S_t\left(1+\hat{\alpha}\right), \qquad n = 1, 3, 6, 9, 12 \tag{2.17}$$

Forecast based on Nickel futures

If the expected future spot price of Nickel is fully reflected in the futures contract, then changes in the price of stainless steel will incorporate changes in its cost which contributes significantly by nickel.

$$\hat{S}_{t+n|t} = \frac{1}{6}F_{t,n}^{Ni}, \qquad n = 1, 3, 6, 9, 12 \tag{2.18}$$

Forecast based on the spread of Nickel futures and stainless steel

An alternative approach to forecasting the spot price is to use the spread between the spot price and the futures price. This spread serves as an indicator of whether the price of stainless steel will likely go up or down. Since stainless steel does not have its own futures market, nickel futures contract will be substituted into the spread. The baseline model was derived from null model of efficiency hypothesis in (2.13),

$$\hat{S}_{t+n|t} = S_t\left(1+\left(-0.89+0.5\ln\left(F_{t,n}^{Ni}/S_t\right)\right)\right), \qquad n = 1, 3, 6, 9, 12 \tag{2.19}$$

The alternative hypothesis is that the spread between nickel futures and stainless steel is either bias, or inefficient, or both bias and inefficient in explaining future spot price of stainless steel. To allow for the possibility that the spread may be a biased predictor, it is common to relax the assumption of a intercept

$$\hat{S}_{t+n|t} = S_t\left(1+\left(\hat{\alpha}'+0.5\ln\left(F_{t,n}^{Ni}/S_t\right)\right)\right), \qquad n = 1, 3, 6, 9, 12 \tag{2.20}$$

Another option is to relax the proportionality restriction which reflects the efficient hypothesis

$$\hat{S}_{t+n|t} = S_t\left(1+\left(-0.89+\hat{\beta}'\ln\left(F_{t,n}^{Ni}/S_t\right)\right)\right), \qquad n = 1,3,6,9,12 \tag{2.21}$$

Finally, we can relax both the unbiasedness and efficiency

$$\hat{S}_{t+n|t} = S_t\left(1+\left(\hat{\alpha}'+\hat{\beta}'\ln\left(F_{t,n}^{Ni}/S_t\right)\right)\right), \qquad n = 1,3,6,9,12 \tag{2.22}$$

2.5.1 Model evaluation

A non rejection of a null hypothesis does not imply that the null model is true and such evidence may not necessarily mean that spot prices are forecastable based on the futures spreads in practice. Chernenko et al. (2004) reported that the hypothesis of forecast efficiency cannot be rejected at conventional significant levels. Elliott et al. (2005) showed that a rejection (or non rejection) of a forecast may depend on the loss function that has been used. They suggested that unless the loss function was known to have symmetric loss, it was important to account for the possible effects of asymmetric loss. For those reasons, predictive accuracy of the above models will be compared against the random walk forecast as the benchmark model under different loss functions such as the mean squared prediction error (MSPE), the mean absolute prediction error (MAPE), bias, and the ability to forecast the direction of the price movement such as the success ratio. The bias is defined as the average amount of the prediction errors. In addition to comparing forecast models by each loss function, it was also necessary to test for the accuracy of the forecasting models. In these tests, the null hypothesis that is a given candidate forecast model, is as accurate as the random walk without drift against the alternative hypothesis that is the candidate model, is more accurate than the no-change forecast. Comparisons of the non-nested model such as equation (2.18) without estimated parameters are based on the DM test of Diebold and Mariano (1995) with the critical values following a standard normal distribution. The nested model comparisons with the estimated parameters such as equation (2.17)and 2.19 are based on Clark and West (2006). The critical values under quadratic loss follow a standard normal while the critical values of absolute loss were estimated using bootstrap method as described in Clark and West. Bootstrap critical values were calculated for quadratic loss and absolute loss under rolling regression estimates of the spread models such as those in equation (2.20), 2.21, and 2.22. Having smaller errors does not mean that the forecaster will be able to predict correctly the direction of price movement. Hence, the success ratio will be used to test the hypothesis that the forecasts fail to predict the observed system. The success ratio was defined as the fraction of forecasts that correctly predict the sign of the change in stainless steel price. The critical value of the sign test was based on Pesaran and Timmermann (1992).

2.5.2 Forecast results

Tables 2.6 to 2.10 assess the predictive accuracy of different forecasting models against the benchmark of random walk without drift for the horizons of 1, 3, 6, 9, and 12 months. The forecast evaluation period is from 1/2002 - 12/20014. These tables report the results for the mean squared prediction error (MSPE), the mean absolute prediction error (MAPE), bias, and success ratio statistic. Only the MSPE and MAPE of the benchmark model were reported in the actual level, all of the MSPE and MAPE results of other forecast models were presented as a ratio relative to the error of the benchmark model. All *p-values* refer to the pairwise test of the null of a random walk without drift.

Table 2.6: One-month ahead forecast error

$\hat{S}_{t+1\|t}$	MSPE (*p*-value)	Bias	MAPE (*p*-value)	Success rate
S_t	42205	9.246	137.27	N/A
$\frac{1}{6}F_{t,1}^{Ni}$	1.7102	-4.018	1.315	0.603
	(0.946)		(0.976)	(0.005)
$S_t\left(1-0.89+0.5\ln\left(F_{t,1}^{Ni}/S_t\right)\right)$	1.710	-4.017	1.315	0.603
	(0.946)		(0.976)	0.005
$S_t\left(1+\hat{\alpha}'+0.5\ln\left(F_{t,1}^{Ni}/S_t\right)\right)$	1.469	23.639	1.213	0.641
	(0.290)		(0.000)	(0.000)
$S_t\left(1-0.89+\hat{\beta}'\ln\left(F_{t,1}^{Ni}/S_t\right)\right)$	1.042	-18.686	1.019	0.491
	(0.281)		(0.314)	(0.533)
$S_t\left(1+\hat{\alpha}'+\hat{\beta}'\ln\left(F_{t,1}^{Ni}/S_t\right)\right)$	0.742	4.404	0.847	0.611
	(0.006)		(0.001)	(0.002)
$S_t\left(1+\hat{\beta}_1\ln(S_t)+\hat{\beta}_2\ln(Ni_t)\right)$	0.698	15.696	0.813	0.617
	(0.000)		(0.000)	(0.001)
$S_t\left(1+\hat{\alpha}+\hat{\beta}_1\ln(S_t)+\hat{\beta}_2\ln(Ni_t)\right)$	0.851	18.817	0.900	0.617
	(0.000)		(0.0167)	(0.002)

Random walk with drift model

Row 2 in Table 2.6 to 2.10 documented that allowing for a drift in most of the cases would not significantly lower the MSPE nor MAPE of the forecast models compared to the random walk forecast. All of the models did not result in any statistically significant improvement in the ability to predict the directions of the changes in stainless steel price. In general, there is no evidence that random walk with drift models dominate the no-change forecast.

Table 2.7: Three-month ahead forecast error

$\hat{S}_{t+3\|t}$	MSPE (*p*-value)	Bias	MAPE (*p*-value)	Success rate
S_t	1.857e+05	26.167	291.29	NA
$S_t\,(1+\hat{\alpha})$	1.122	39.549	1.089	0.436
	(0.082)		(0.059)	(0.938)
$\frac{1}{6}F^{Ni}_{t,3}$	1.302	0.033	1.260	0.635
	(0.833)		(0.963)	(0.000)
$S_t\left(1-0.89+0.5\ln\left(F^{Ni}_{t,3}/S_t\right)\right)$	0.478	25.477	0.735	0.628
	(0.024)		(0.016)	(0.000)
$S_t\left(1+\hat{\alpha}'+0.5\ln\left(F^{Ni}_{t,3}/S_t\right)\right)$	0.489	6.038	0.768	0.705
	(0.000)		(0.000)	(0.000)
$S_t\left(1-0.89+\hat{\beta}'\ln\left(F^{Ni}_{t,3}/S_t\right)\right)$	0.982	-40.034	0.981	0.601
	(0.083)		(0.145)	(0.005)
$S_t\left(1+\hat{\alpha}'+\hat{\beta}'\ln\left(F^{Ni}_{t,3}/S_t\right)\right)$	0.548	-4.726	0.796	0.669
	(0.004)		(0.001)	(0.000)
$S_t\,(\beta_1\ln(S_t)+\beta_2\ln(Ni_t))$	0.459	14.507	0.743	0.687
	(0.000)		(0.000)	(0.000)
$S_t\,(\alpha+\beta_1\ln(S_t)+\beta_2\ln(Ni_t))$	0.759	22.870	0.774	0.705
	(0.000)		(0.000)	(0.000)

Nickel futures model

The third row in table 2.6-2.10 presented the results of nickel futures as direct predictors for stainless steel. It is easily seen that nickel futures produces smaller error compared to the random walk model for horizons longer than 3 months. However, these results are not statistically significant. Also, the success ratios suggest that nickel futures prices have failed to predict the correct movements of stainless steel price at any time horizon longer than 6 months.

Table 2.8: Six-month ahead forecast error

$\hat{S}_{t+6\mid t}$	MSPE (p-value)	Bias	MAPE (p-value)	Success rate
S_t	4.7625e+05	54.149	456.37	NA
$S_t\left(1+\hat{\alpha}\right)$	1.164	122.23	1.096	0.410
	(0.133)		(0.085)	(0.959)
$\frac{1}{6}F_{t,6}^{Ni}$	0.7092	52.582	0.941	0.506
	(0.212)		(0.367)	(0.312)
$S_t\left(1-0.89+0.5\ln\left(F_{t,6}^{Ni}/S_t\right)\right)$	0.614	75.553	0.900	0.526
	(0.041)		(0.133)	(0.186)
$S_t\left(1+\hat{\alpha}'+0.5\ln\left(F_{t,6}^{Ni}/S_t\right)\right)$	0.399	118.640	0.608	0.86
	(0.000)		(0.000)	(0.000)
$S_t\left(1-0.89+\hat{\beta}'\ln\left(F_{t,6}^{Ni}/S_t\right)\right)$	0.322	-101.99	0.585	0.861
	(0.000)		(0.000)	(0.000)
$S_t\left(1+\hat{\alpha}'+\hat{\beta}'\ln\left(F_{t,Ni}^{Ni}/S_t\right)\right)$	0.351	65.693	0.569	0.874
	(0.003)		(0.000)	(0.000)
$S_t\left(\beta_1\ln\left(S_t\right)+\beta_2\ln\left(Ni_t\right)\right)$	0.519	-3.589	0.780	0.713
	(0.037)		(0.056)	(0.000)
$S_t\left(\alpha+\beta_1\ln\left(S_t\right)+\beta_2\ln\left(Ni_t\right)\right)$	0.486	14.371	0.691	0.783
	(0.000)		(0.000)	(0.000)

Spread models

The rolling regression using the spread of nickel futures and stainless steel to forecast the future price of stainless steel with the rolling window of 12 months. Rows 8-11 in Tables 3-7 show that spread forecasts have lower MSPE than no-change forecast at all horizons except in a 1 month ahead forecast. The test statistics for all horizons from 3 to 12 months show statistical significance in forecast performance of the spread-based model which the cost structure of stainless steel is accounted. Looking at MAPE criteria, the spread models also perform better for all horizons but 1 month. However, the non-estimated parameter spread models statistically perform well only in 3 and 6 month horizons while the relaxed models' performances are statistically better at horizons from 3 to 12 months. These results could be explained by the technique behind the OLS regression learning which aims to minimize squared errors. Finally, the results reveal some evidence that spread models help predict the direction of change at all horizons including the 1-month horizon.

Table 2.9: Nine-month ahead forecast error

$\hat{S}_{t+9\|t}$	MSPE (*p*-value)	Bias	MAPE (*p*-value)	Success rate
S_t	8.123e+05	76.722	611.54	NA
$S_t\left(1+\hat{\alpha}\right)$	1.238	218.21	1.138	0.411
	(0.189)		(0.151)	(0.926)
$\frac{1}{6}F_{t,9}^{Ni}$	0.751	129.923	0.9852	0.500
	(0.165)		(0.449)	(0.367)
$S_t\left(1-0.89+0.5\ln\left(F_{t,9}^{Ni}/S_t\right)\right)$	0.760	128.97	0.943	0.512
	(0.054)		(0.180)	(0.266)
$S_t\left(1+\hat{\alpha}'+0.5\ln\left(F_{t,9}^{Ni}/S_t\right)\right)$	0.648	-5.091	0.840	0.748
	(0.000)		(0.000)	(0.000)
$S_t\left(1-0.89+\hat{\beta}'\ln\left(F_{t,9}^{Ni}/S_t\right)\right)$	0.803	-132.890	0.945	0.695
	(0.039)		(0.076)	(0.000)
$S_t\left(1+\hat{\alpha}'+\hat{\beta}'\ln\left(F_{t,9}^{Ni}/S_t\right)\right)$	0.717	-18.609	0.829	0.722
	(0.039)		(0.021)	(0.000)
$S_t\left(\beta_1\ln\left(S_t\right)+\beta_2\ln\left(Ni_t\right)\right)$	0.632	21.473	0.798	0.755
	(0.237)		(0.241)	(0.000)
$S_t\left(\alpha+\beta_1\ln\left(S_t\right)+\beta_2\ln\left(Ni_t\right)\right)$	0.389	62.047	0.564	0.914
	(0.000)		(0.000)	(0.000)

Table 2.10: Twelve-month ahead forecast error

$\hat{S}_{t+12\|t}$	MSPE (*p*-value)	Bias	MAPE (*p*-value)	Success rate
S_t	1.136e+6	94.289	741.770	NA
$S_t\,(1+\hat{\alpha})$	1.317	312.230	1.186	0.324
	(0.208)		(0.241)	(0.999)
$\frac{1}{6}F^{Ni}_{t,12}$	0.805	196.546	0.997	0.455
	(0.112)		(0.487)	(0.708)
$S_t\left(1-0.89+0.5\ln\left(F^{Ni}_{t,12}/S_t\right)\right)$	0.838	137.000	0.966	0.461
	(0.041)		(0.239)	(0.679)
$S_t\left(1+\hat{\alpha}'+0.5\ln\left(F^{Ni}_{t,12}/S_t\right)\right)$	0.677	15.167	0.861	0.772
	(0.000)		(0.000)	(0.000)
$S_t\left(1-0.89+\hat{\beta}'\ln\left(F^{Ni}_{t,12}/S_t\right)\right)$	0.738	-53.227	0.888	0.751
	(0.031)		(0.051)	(0.000)
$S_t\left(1+\hat{\alpha}'+\hat{\beta}'\ln\left(F^{Ni}_{t,12}/S_t\right)\right)$	0.657	12.988	0.822	0.821
	(0.042)		(0.024)	(0.960)
$S_t\,(\beta_1\ln(S_t)+\beta_2\ln(Ni_t))$	0.562	56.369	0.776	0.834
	(0.317)		(0.354)	(0.000)
$S_t\,(\alpha+\beta_1\ln(S_t)+\beta_2\ln(Ni_t))$	0.358	165.290	0.515	0.910
	(0.001)		(0.000)	(0.000)

The results are consistent with our efficiency test above. The forecasting model (2.19) does dominate the no-change forecast in MSPE criterion at any horizon longer than 1 month. However, imposing this null does not dominate the no-change forecast in criteria such as MAPE and success rates at the horizon of 9, and 12 months. This provides the evidence supporting the concern of Chernenko et al. that the forecast efficiency cannot be rejected at conventional significance levels. It echoes Elliott et al. (2005) that forecast efficiency tests tend to be biased in favor of the null hypothesis if loss function coincides with the econometrician's loss function which is the mean squared error in OLS. As mentioned above, there is some bias associated with using nickel to forecast stainless steel. Thus, we have tried to remove the cross-forecasting bias before testing by subtracting for the mean difference in prices of nickel and stainless steel. Nonetheless, we might not remove all of that bias due to the variation in nickel and stainless steel prices. By relaxing the bias restriction, model (2.20) accounts for the possible cross-forecasting bias by estimating the intercept of the model. Model (2.20) produces the lowest MSPE, MAPE, bias, and highest success rate among spread models most of the time. It could be confirmed that nickel is an efficient but bias predictor for stainless steel. This bias in forecasting is unavoidable due to the differences in prices of nickel and stainless steel.

2.6 Conclusion

Full cost pricing scheme, specifically the surcharge system, has tied the components costs, especially nickel, to the price of stainless steel and completely changed the formation of stainless steel price. Without surcharges, the price movement of stainless steel was determined strongly by the supply and demand factors. After surcharges were applied in 2000, among all of the material components of stainless steel, nickel price plays a key role in determining the movement of stainless steel price. Despite the fact that energy cost contributes significantly to the cost of stainless steel, energy price, specifically coal price in this case, does not help explain stainless steel price at all. Chromium accounts for roughly 16 percent of stainless steel cost but only contributes modestly to the rise of stainless steel price during the period of 2007 to 2009. However, it plays a major part in the plunge of stainless steel price in 2009 until the end of that year. Besides those periods, chromium does not help explain the fluctuation of stainless steel. And iron does not attribute to changes in stainless steel price at all even though iron is the main component in steel. While the component costs determine the magnitude of the contribution, the component volatility are the key role in setting the course of stainless steel price movement. Since nickel is the most volatile cost, it is a primary force driving steel price.

Changes in expectation of nickel price and production had been shown to have a significant impact on the determination of the stainless steel price and production since it became a key contributor to the movement of stainless steel price. The market efficiency hypothesis test confirmed that nickel futures rates could efficiently predict the price of stainless steel for all horizons longer than 1 month after accounting for price differences between nickel, stainless steel, and the cost structure of stainless steel. Nickel also seemed to be used as a reference in production planning and purchase scheduling of stainless steel. Causality revealed that nickel production has been driving stainless steel production starting from 2002.

Moreover, the ability of nickel to accurately forecast stainless steel price is the top concern since it addresses the prospect of using nickel to manage stainless steel price risk. A non-reject result of efficiency hypothesis does not mean that nickel is an accurate predictor of stainless steel since efficiency tests may favor the null hypothesis when the loss function under the null hypothesis is the same as the econometric loss function. To tackle this issue, the real-time out-of-sample forecasts were performed using spreads in nickel futures and stainless steel and the results were then compared with random walk forecast under various loss functions. A production of forecasts using the nickel futures price and the random walk with an estimated drift to compare with the spread model was done. The out of sample forecast of spread models were consistent with efficiency tests under the MSPE metric. However, the null spread model did not dominate random walk forecast under MAPE criterion for horizon 9, and 12 months. This confirmed the concern of non-rejection bias due to MSE being a loss function of OLS. The non-rejection in real-time forecasting has also substantiated the time-varying relationship between nickel and stainless steel, and hence removing the bias by subtracting for the average difference in price did not eliminate that bias completely. When take into account of time-varying bias, model equation (2.20) produced the lowest MSPE, MAPE, bias, and higher prediction success rate among all model. The results confirmed that the spread model produced the most accurate forecast in most of the cases by allowing for the bias to vary. This bias is a result of differences in prices of stainless steel and its predictor, nickel and is not a premium risk as described in Fama (1984).

The next question that worth to study is whether the steel industry should pass the entire price risk to their customers. Since the commodity components are highly correlated, the steel industry may only need to pass through the costs of the components that are highly volatile such as nickel or chromium. Moreover, the higher price volatility would affect consumer's order quantity which consequently affects a firm's production planning and its efficiency. Moreover, surcharge practice could invite competition form abroad since import product prices are fixed. If consumers are risk averse, they may turn to importers to avoid the price risk.

Chapter 3

Government's interventions in the futures market and unintended consequences

The interventions of China government provided an interesting natural experiment on the futures market in which two different steel contracts, reinforced bar (rebar) and hot rolled coil (HRC), both reflected the same fundamentals but were subjected to different degrees of regulations. These interventions impact trading activities and market quality of both contracts. The intervention mechanism shows that the deteriorating market quality of the HRC was the results of increasing volatility due to the speculation of government intervention in the rebar market. Speculative activities lead to stronger comovement between these two contracts and less informative in their prices. We also found evidence of informed trading activities in the market. Higher trading volume and lower open interest indicate the intervention announcement in the next day.

3.1 Introduction

Government intervention in financial markets is not a new story. Interventions could be one-in-a-life-time events with the purpose to stabilize markets such as the short-selling ban in the U.S. during 2008 financial crisis or China meddling in its stock market during 2015 market meltdown to prevent the market collapse. They could also be implemented at regular frequencies to direct markets toward governments' goals such as trading in foreign exchange market to control the exchange rate. These interventions were proposed with a good intention to stabilize the market, but they often resulted in unintended consequences that may exacerbate, rather than improve, market quality and the information efficiency of asset prices (Battalio et al., 2012; Pasquariello, 2017). However, studying effects of those interventions often posed a challenge in drawing a causal effect due to the lack of a control group. In the case of short-sell ban in the U.S. during 2008, the effects of short-sell ban was drawn from the comparison between stocks in the short-selling ban list with those were not subjected to the ban (Boehmer et al., 2013; Brogaard et al., 2017). However, these stocks represented different companies and had different underlying fundamentals. For that reason, most of the studies were not able to pinpoint the mechanisms behind the interventions and often stopped short at addressing the effects of interventions. Therefore, the purpose of this paper is to identify not just only the effects but also the mechanism causing those effects.

This paper intended to address those questions by examing the effects of China government intervention into its futures market, especially for the steel futures. There are currently two steel contracts listed on Shanghai Futures Exchange (SHFE) which are the reinforced bar (rebar) and the hot rolled coil (HRC). They are both offered with one year expiry. These two contracts have different liquidities as rebar contracts are traded ten times more often than HRC contracts with total volume of approximately 4 million compared to 300 thousands of the HRC. Since the rebar contracts were more frequently traded, they were heavily subjected to government intervention during the 2016 commodity bubble while HRC contract were not. This adventure provides an interesting natural experiment on the financial market which would not be able to observe elsewhere in the such a way that the treatment and the control group of assets share the same fundamental. The government intervened into the futures market through frequent policy changes by using a wide array of policy tools ranging from trading quota, raising fees and trading margins, or cutting the number of new positions allowed daily. Traders and investors who violated these policies would be temporarily blocked or suspended from trading. These interventions are not passive in nature like the short-sell ban in the U.S. and hence could make the situation more complicated. Another interesting fact about the steel futures market that is worth to point out is its growing trading activities. Rebar contracts has surpassed WTI contracts to become the most traded commodity in 2016.

We used the official announcement on the SHFE to study the impact of the intervention policy on the market. Government interventions were shown to increase the trading activity and worsen market quality. The rebar contract has shown to have jumps in trading volume and drops in the position tenure rate (PTR) when interventions were announced. These abnormalities in trading activity were not pronounced in the HRC contract. However, the impacts of the interference on market quality present on both of the contracts. Volatility, price impact, and bid-ask spread were all increased when the intervention news was published. Studying the mechanism of the intervention effects is more important than determining the impacts because it allows the policymaker to change the outcomes by adjusting their ploicies and actions. Nevertheless, most of the previous studies stopped short at determining the impacts. Determining the mechanism of impacts is not a simple task since we need to consider all of the possibility of the interactions among intervention, trading activities, and market quality factors. One way to study the connection among different factors is using Granger-causality network as suggested by Billio et al. (2012). Nonetheless, Billio et al. method only considers the direct pairwise causal relationship and neglects the latent confounders. Moreover, Payzan-LeNestour and Bossaerts (2015) confirm that investors learn in a Bayesian way when they nudged. Hence, Bayesian causal network would appropriately adress the latent confounding factors and they way traders learn when their payoffs are shifted by the government interference. The intervention mechanism confirm the direct effects of government policies on the PTR, volatility, and bid-ask spreads but trading volume. The increasing trading volume was caused by the fear of holding on inventory induced by the uncertainty of government interventions. On the other hand, the mechanism network reveals that there are no direct effects of interventions on bid-ask spread as suggested in the regression. Interventions in rebar market could have a spillover effect on the volatility of the HRC market, which in turn impacts the bid-ask spread. Higher volatility and trading cost have prompted speculations of investors on the government actions that lead to irregularity in trading volume. An evidence of speculation is the increase comovement of the two contracts contract around the anouncement days.

An increaseing comovement of rebar and HRC contracts one day before the announcement also raise a suspicion of insider trading. Security officials using insider knowledge to make profit for themselves or to enrich friends and family are a pervasive issue in China. Investors with insider information would act ahead of government moves. Hence, to verify whether there are insider trading activities in the market, we test the ability of the trading activities to predict the probability of intervention. Abnormally higher trading volume and lower open interest in a past day are statistically significant indicator of the intervention in a next day.

In the next session, we will give an overview of the steel futures market of China and around the world. Section 3 will discuss intervention policies and their impacts that have been documented in the literature. Section 4 will present the Madhavan et al. (1997) (MMR) model, and its estimates of various market quality factors such as price impact and implied bid-ask spread. The following section, Section 5, will analyze the impacts and the mechanism of the interventions. Finally, Section 6 will give a conclusion remark and policy implications of the findings.

3.2 Overview of steel market and steel futures market

Steel is a critical material which is widely used in practically every industry including construction, automobiles, machinery, appliances, energy, and more. Steel is produced in most countries globally and is heavily a traded commodity. Global crude steel production has been growing for most of the last decade. Total steel production was just more 1.1 billion metric tons in 2005 had grown up to 41.4 percent to 1.6 billion to 1.6 billion metric tons in 2015 - an increase of 475 million metric ton over ten years. Exports of steel products have shown an upward trend in the past several years. Global exports increased by 20.6 percent to 446 million metric tons between 2005 and 2007 before dropping through the global financial crisis period during 2008-2009. By 2009, exports had plummetted by 26.2 percent from 2007, a decrease of 116.6 metric tons. Market recovery in 2010 led to an increase of 21.3 percent in global steel exports. Global exports increase every year after that with the exception of 2013. Just as the total amount of global steel exports changed between 2005 and 2015, there were also significant fluctuations in the volume of steel product imported globally. Imports grew 21.9 percent from 2005 to a peak of 436.4 million metric tons in 2007. As with production, apparent use, and exports, imports also dropped in 2009, a 30.2 percent down from 2007 due to the global financial crisis. As market improved and trade recovery, steel import quickly rose to 436 million metric tons by 2012, on par with pre-financial crisis 2007 levels. However, imports level delined in 2013 and again in 2015. [1]

The underlying asset value of the global steel industry is enormous with the estimated value of about $420bn compared to $162bn of base metals and is on a growing trend[2]. Nevertheless, steel remained one of the few major commodities without a futures contract. With the rising demand, the price of the HRC - the most common steel product - has risen 195% from 2000 to its peak in 2008. Since steel is usually sold directly by steelmakers to large customers or through middlemen such as metal service centers, steel buyers have fewer mechanisms to manage their risks during periods of price volatility. That has left many buyers to rely on less-effective means to manage risk. For example, Craig T. Bouchard, president of Chicago-based Esmark, says his steel-services company this year began using a basket of stocks, bonds, derivatives and commodities that roughly tracks steel prices.

In response to the growing calls for a better risk management tool for steel, many major commodity exchanges had planned to establised steel futures markets. The New York Mercantile Exchange (NYMEX) is the pioneer and the most vocal support for a steel futures market. In 2007, Robert Levin, senior vice president of the NYMEX, announed plans to launch a regional, cash-settled contract for US hot-rolled coil (HRC) based on SteelBenchmarker by the end of the year. He said Nymex had the technology in place "to just plug it in and launch" but wanted to make sure enough industry members were ready to participate[3]. However, NYMEX had not its first steel product launched until it was obsorpted

[1] World Steel in Figure 2016. World Steel Association.
[2] Trade statistics for international business development. Trade Map 2015
[3] American Metal Market's Guide to Steel Futures. American Metal Market

by Chicago Mercantile Exchange (CME), the world largest derivative exchange. After merging with NYMEX, CME started to offer its U.S. Midwest domestic HRC steel futures contract in October 2008. The London Metal Echange (LME), in April 2008, launched two physical-delivered futures contracts for steel billet: Mediterranean with initial delivery point in Turkey, and Far Eastern with initially delivery point in South Korea. Trading activity on Med contract soared 385 percent to 57,606 lots in the first six months of the year, equivalent to 3.74 million tonnes of steel, accounting for around 0.6 percent of the world's total billet production in 2009. Despite of the uptick at the beginning, LME billet contract failed largely due to problem associated with storing and withdrawing steel from backlogged warehouses. These contracts were merged to create a global one under the Mediterranean contract in July 2010. LME later in November 2015 offered two new cash-settled contracts: one for steel reinforcing bar and one for steel scrap. Quickly joining the pack, Shanghai Futures Exchange (SHFE) began offering two construction steel products: reinforcing bar and wire rod in April 2009. SHFE introduced hot-rolled coil contract in 2014.

As financial markets race to grab a larger share of steel futures trading, big steel producers remain opposed to the idea, while smaller, medium-sized mills warm to it. Producers often resist having their resources pegged to futures contracts, fearing they will lose the power to set prices, commodity experts say. "It's the same thing we've seen in aluminum, nickel, and copper in the '70s and '80s," said Jeffrey Christian, managing director of the commodity research and consulting firm CPM Group. The Washington-based American Iron and Steel Institute and major domestic companies such as Pittsburgh-based U.S. Steel Corp. have previously said they don't support a steel future, though U.S. Steel President John Surma said recently, "if enough people want to have a price-management mechanism, I think that will happen." New York financier Wilbur Ross, chairman of one of the nation's largest steel companies, Cleveland-based International Steel Group Inc., favors steel futures. "I'm in favor of anything that reduces volatility," he said recently. "If I were a steel service center, I would like to have something to hedge my risks."That raised the skepticism from experts about the success of steel market in part because they lack the backing of steelmakers and industry associations. Moreover, steel doesn't fit the traditional definition of a commodity as an unprocessed, freely tradable material. Rather, steel is an alloy of iron, coke and, in some cases, other metals. "Steel is a semifinished product," said economist James Glassman, of J.P. Morgan Securities. "It's got some of the qualities of a commodity, in the sense that it's widely used and tradable. But it's also got some labor costs and other factors priced in."

Among the steel futures market, SHFE was the most active market. However, the issue arose when the influx of day traders headed to commodity market to search for higher returns. The total volume of steel futures on SHFE surpassed all shares traded on China's equity markets in April 2016[4]. The exploding of trading activities recently in commodity markets had prompted China's authorities scrambling to prevent markets from melting down. It is not unusual that China government actively manages its financial markets in order to promote financial stability. They had stepped in to calm down the turmoil in its stock markets in 2015 by buying back stock, lowering interest rate, imposing a moratorium on initial public offerings, and suddenly devaluating the yuan. Those interventions raised doubts about the government's ability to manage its overheating financial system and have been a great source of anxiety for investors and policymakers around the globe. This time, China government did so through frequent policy changes by using a wide array of policy tools ranging from setting quota, raising fees and trading margins, cutting the number of new positions allowed daily, temporarily suspending traders' accounts or blocking suspicious trading activities. These interventions were started with the announcement of higher trading fee on March 8, 2016. Besides raising the trading fee, China government simultaneously set higher trading margins, imposed a quota on position, and limiting transactions in hope of slowing down trading activities. However, the government did not have the commitment power or those efforts seemed not to be effective, trading volume spiked again. On June 1, 2016, SHFE announced that it will enforced quota on the number of transactions and will close any position that exceeds the limit. Besides the trading fee, all of other interventions were targeting traders and trading activities of the rebar contract.

The following section is a literature review. Section 4 estimates the bid-ask spreads of the futures contracts using Madhavan et al. (1997) model. Section 5 examines the effects of goverment interventions. Section 6 analyze the mechanisms of the interventions. Finally, section 7 concludes with some additional discussion.

[4]https://www.ft.com/content/592c8af4-0b94-11e6-b0f1-61f222853ff3

3.3 Literature review

The impact of government intervention on asset prices and the macroeconomy is well documented in the literature. However, studies on the effects of government interventions in financial markets are quite limited. The extent of these studies was confined to either static policies such as the short-sale ban or dynamic intervention by participating in the market such as government trading in the foreign exchange market. China's interventions in the futures market presented another way of how a government could intervene by using a host of policies to actively shaping the course of the market. The dynamic angle of these policies could make the situations and the effects of intervention more complicated compared to the fixed policy. Nonetheless, the pass studies could provide some insight into the possible effects of the China intervention in its futures market.

The most recent government intervention in financial market using fixed policy discussed in the literature is the short-sale ban implemented by the US Securities and Exchange (SEC) in September 2008. During the 2008 financial crisis, the US SEC decided to temporarily disallow short-sale of nearly 1,000 financial stocks. Using proprietary NYSE data, Boehmer et al. (2013) constructed a difference in difference tests by comparing 200 stocks on the ban list to 1,066 non-banned stocks to examine the impacts of the ban. Boehmer et al. (2013) showed that the market quality of stocks subjected to the ban deteriorated severely. The short-sale ban was shown to associate with larger bid-ask spread and higher intraday price volatility. Brogaard et al. (2017) raised the concern that the ban could be correlated directly with changes in liquidity unrelated to short selling since the stocks selected for the ban in Boehmer et al. (2013) were not randomly selected. Thus, to mitigate the concern, Brogaard et al. (2017) examined the effects of the ban on the high frequency trading (HFT) and non-HFT using NASDAQ data. They found that HFTs' trading and HFT's short selling harm liquidity by adversely selecting liquidity supplier while non-HFTs' short selling activity improves liquidity. The ban has largely eliminated HFTs' shorting activity but it has a smaller impact on the overall HFT activity. However, Brogaard et al. (2017) doubted that limiting HFTs' ability to demand liquidity might not improve overall market liquidity since it could impair HFTs' ability to manage risk and thereby supply liquidity. The short-selling ban not only had detrimental effects on the ban stocks but also had adverse effects on the option market. The ban caused option trading costs increase sharply and lead to the bias in the relative prices of options and stocks on the ban list.

Another policy that was often used to control market was daily price limit. It was wildly adopted as a market stabilization tool. However, this tool has been shown to have a counterproductive effect. Chen et al. (2018) showed that the daily price limit induced large investors in Shenzhen Stock Exchange to pursue a destructive strategy of pushing stock prices up to the upper limit and then selling on the next day.

Besides policies, governments also often participated in the market to steer the market to the desired direction. Central banks around the world occasionally intervene in the foreign exchange markets to control the exchange rates. Naranjo and Nimalendran (2000) showed that government interventions created significant adverse selection problems for dealers. They found that the bid-ask spread of the DM/US$ exchange rate increased with the intervention during the period 1976-1994. This effect only occurred when the interventions were unexpected. Government interventions affect not only the trading cost but also the attention to market information. Peiers (1997) used Reuters screen headlines of central bank intervention as an information trigger to identify asymmetric information flows and price leadership patterns in the DM/US$ exchange market. The results revealed that Deutsche Bank was treated as a price leader up to 60 minutes prior to intervention report. By the time of Reuters announcement, traders resumed their preintervention trading interactions. Pasquariello (2017) reported evidence of violations of the law of one price in arbitrage-related markets induced by direct government intervention in the market.

Besides studies on different specific incidents of government interventions, Brunnermeier et al. (2017) laid out a theoretical framework of the way China managing its financial system. Government intervention aiming to prevent market breakdown and volatility explosion could alter market dynamics by introducing noise that drives asset prices and could divert investor attention toward acquiring information about this noise factor rather than fundamentals. Hence, government intervention could exacerbate the information efficiency of asset prices.

3.4 A structural model of price formation

We first need to estimate the key market quality factor such as price impact and bid-ask spread. We do so by examining the SHFE tick data using a prototypical microstructure model of Madhavan, Richardson, and Roomans (1997) (MRR). The MRR model provides insights into the determinants of the autocorrelations of quotes and returns as well as the price impact and the variance of bid ask spread and order flow.

3.4.1 MRR model

Consider the market for a risky security whose fundamental value evolves through time. The security is traded in an auction-dealer mechanism where liquidity providers quote bid and ask prices at which they are willing to trade. An order also may be executed within the quotes. Let p_t denote the transaction price of the security at time t. $x_t$denotes an indicator variable for trade initiation, where $x_t = +1$ if trade t is buyer initiated and -1 if the trade is seller initiated. Denote by ε_t the innovation in beliefs between time t-1 and t due to new public information. ε_t is assumed to be an independent and identically distributed random variable with mean zero and variance σ_ε^2. MRR assumes that traders have private information that can affect fundamental asset values, which would otherwise follow a random walk. Let $\mu_t$denote the post-trade expected value of the stock conditional upon public information and the trad initiation variable. The revision in beliefs is the sum of the change in beliefs due to new public information and order flow innovation.

$$\mu_t = \mu_{t-1} + \theta\left(x_t - E\left[x_t|x_{t-1}\right] + \varepsilon_t\right) \tag{3.1}$$

If market makers believe that some traders possess private information about fundamental asset value, a buy (sell) order is associated with an upward (downward) revision of beliefs. The change in beliefs due to order flow is $\theta\left(x_t - E\left[x_t|x_{t-1}\right]\right)$, where $\left(x_t - E\left[x_t|x_{t-1}\right]\right)$ is the surprise in order flow and $\theta \geq 0$ measures the degree of information asymmetry or the so-called permanent impact of the order flow innovation. Higher values of θ indicate larger revisions for a given innovation in order flow.

Market maker bid and ask quotations are ex post rational so that the ask (bid) price is conditioned on a trade being initiated (seller initiated). Let p_t^a, p_t^b denote the (pre-trade) ask price, and bid price at time t respectively. Let$\phi \geq 0$ represent the market maker's cost per share for supplying liquidity. We can interpret ϕ as the dealer's compensation for transaction costs, inventory costs, risk bearing, and possibly the return to their unique position.

$$p_t^a = \mu_{t-1} + \theta \left(1 - E\left[x_t | x_{t-1}\right]\right) + \phi + \varepsilon_t \tag{3.2}$$

$$p_t^b = \mu_{t-1} - \theta \left(1 + E\left[x_t | x_{t-1}\right]\right) - \phi + \varepsilon_t \tag{3.3}$$

θ captures the temporary (transitory) effect of order flow on prices. Orders can be executed at the quoted bid or ask price, and sometimes within the bid-ask spread. In the later case, transactions are assumed to be executed at the midquote, $\left(p_t^a + p_t^b\right)/2$. Then the transaction price can be expressed as

$$p_t = \mu_t + \theta x_t + u_t \tag{3.4}$$

where u_t is an independent and identically distributed random variable with mean zero. The term $u_t$captures the effect of stochastic rounding errors included by price discreteness or possibly-time varying returns. Any systematic deviation from zero in the rounding error is captured in the dealer cost component ϕ. Dealer must incorporate the transaction cost ϕ into the quotes. Therefore, the transaction price at time t has already impounded the effect of the trade direction on the incoming trade.

$$p_t = \mu_{t-1} + \theta \left(x_t - E\left[x_t | x_{t-1}\right]\right) + \phi x_t + u_t + \varepsilon_t \tag{3.5}$$

MMR assumes that the trade initiation variable follow a Markov process. The probability that a transaction at the ask(bid) follows a transaction at the ask (bid) is

$$\gamma = \Pr\left[x_t = x_{t-1} | x_{t-1} \neq 0\right] \tag{3.6}$$

The first order autocorrelation of the trade initiation variable is $\rho = E[x_t|x_{t-1}]/Var[x_{t-1}] = 2\gamma - (1-\lambda)$, with lambda is the probability of a midquote execution. When there is no possibility of transacting within the quotes, $\lambda = 0$. Then the conditional expectation of the trade initiation variable given public information are

$$E[x_t|x_{t-1} = +1] = \gamma - (1-\gamma) = \rho$$

$$E[x_t|x_{t-1} = -1] = (1-\gamma) - \gamma = -\rho$$

thus the conditional expectation $E[x_t|x_{t-1}] = \rho x_t$.

equation (3.5) can be expressed as

$$p_t - p_{t-1} = (\phi + \theta)x_t - (\phi + \rho\theta)x_{t-1} + \varepsilon_t + u_t - u_{t-1} \tag{3.7}$$

$$\Delta p_t = (\phi + \theta)x_t - (\phi + \rho\theta)x_{t-1} + \xi_t \tag{3.8}$$

where $\xi_t = \varepsilon_t + u_t - u_{t-1}$ is a composite of public information and microstructure noises. ξ_t is assumed to be an independent and identically distributed random variable with mean zero and variance σ_ξ^2.

The parameters governing the behavior of transaction prices and quotes, the asymmetric information parameter, θ, the cost of supplying liquidity, ϕ, and the autocorrelation of the order flowρ, can be estimated by the generalized method of moments (GMM) with the population moment conditions implied by the model

$$E\begin{pmatrix} x_t x_{t-1} - x_t^2\rho \\ \xi_t \\ \xi_t x_t \\ \xi_t x_{t-1} \end{pmatrix} = 0 \tag{3.9}$$

where $\xi_t = \Delta p_t - (\phi + \theta)x_t - (\phi + \rho\theta)x_{t-1}$. The first equation is the definition of the autocorrelation in trade initiation. The second equation defines the pricing error. the last two equation are the OLS normal equations.

The implied bid-ask spread is $2(\theta + \phi)$ and the price impact for a buyer initiated trade is $\theta(1+\rho)$.

3.4.2 Parameter estimates

3.4.2.1 Data

The data used in this study include the tick data of transaction prices, daily volumes, and open interest of reinforced bar (rebar) and hot rolled coil (HRC) steel contracts traded on SHFE during 2016 and 2017. This data could be obtained from the Bloomberg terminal. All the contracts for both rebar and HRC product have the expiry of 1 year. The two most traded contracts of these two products, contracts with October expiration, were selected to examine the evolution of the information parameters over the trading lives of these contracts. The trade directions were classified based on the tick rule. The volatility was estimated based on 1-minute price data.

Since SHFE trading hours are from 9:00 to 11:30 and from 21:00 to 3:00 of the next day, the data would be divided into two periods to avoid distortion in estimates due to new information arriving during the break that could cause prices to jump. From now on, the trading period from 9:00 to 11:30 will be called the morning session, and the period from 21:00 to 3:00 is the night session. Also, to ensure there are sufficient observations for model estimation, only trading sessions which have at least 100 trades per period are considered.

3.4.2.2 Parameter estimates

Table 3.1 and 3.2 present summary statistics on the individual parameter estimates governing the stochastic process for the transaction price changes of rebar and HRC contracts with October 2016 expiry on the SHFE. The tables present the mean coefficient estimates and the mean standard errors of the estimated parameters for these two contracts in a one-month interval for the eleven months leading to the expiry of them. The daily values will be the average of the morning and the night sessions since there is no significant difference between the estimates of these two trading sessions for each contract. It is noticeable that all of the standard errors are relatively small compared to their estimates showing the reliability of these estimates.

The information asymmetry, θ, is the main parameter of interest. From table 3.1, it is clear that the degree of asymmetry for the rebar contract decreased for the first four months of its life before increased from March through July, then decreased again the life of the contract. On the other hand, θ of the HRC contract continually dropped over three quarters of its life as trading activities increased and only climbed back up when trading was fading (see table 3.2). θ represents the magnitude of the revision in the market maker's beliefs concerning the security's value induced by order flow. A decline in θ represents less reliance on the signal content of order flow. The greater reliance on prior beliefs is consistent with either market maker learning about fundamental asset value through the trading process, or a larger percentage of liquidity traders.

The transaction cost ϕ increased over the life of the rebar contract. It increased an average of 19 cents from October to July for both session, a rise of about 46 percent, before slightly decreased. On contrary, the transaction cost of HRC contract decreases gradually through its life. On average, the trading cost of the morning session and the night session decreased 94 cents from 1.52 to 0.58 and 15 cents from 0.70 to 0.55 respectively during January through September period. The transaction cost ϕ represents the economic cost of market making, and the increase in this parameter reflects the increasing risks associated with carrying inventory.

The autocorrelation of order flow ρ of rebar contract gradually declined and became negative from March to August. The negative sign of order flow autocorrelation suggests that traders will liquidate their positions once price moves up (down) rather than piling up or hold on to their positions. The negative autocorrelation of order flow reflects the higher transaction cost and the higher risk of carrying inventory. For HRC contract, ρ is positive and has a U-shape pattern. This suggests that order flow plays an important in determining the direction of the price of the HRC contract.

The price impact of trades to the rebar contract initially decreased from December through February. It then increased when the interventions were rolled out. On the other hand, the price impact of the HRC contract decreased throughout its life.

Table 3.1: The GMM model parameter and trading cost estimates of rebar futures contract expired 10/2016

	θ	ϕ	ρ	J-test	S^{MRR}	r	Price Impact
November	0.137	0.437	0.690	1.377	1.1486	0.2367	0.2332
	(0.002)	(0.026)	(0.024)	(0.450)	(0.0021)	(0.0009)	
December	0.098	0.442	0.588	1.564	1.0816	0.1811	0.1553
	(0.011)	(0.011)	(0.022)	(0.455)	(0.0003)	(0.0003)	
January	0.097	0.453	0.501	1.613	1.1011	0.1754	0.1452
	(0.009)	(0.009)	(0.023)	(0.398)	(0.0002)	(0.0001)	
February	0.082	0.469	0.348	2.063	1.1013	0.1478	0.1099
	(0.007)	(0.006)	(0.022)	(0.407)	(0.0001)	(7.83E-05)	
March	0.221	0.549	-0.051	4.439	1.5411	0.2710	0.2062
	(0.012)	(0.009)	(0.016)	(0.322)	(0.0010)	(3.28E-05)	
April	0.280	0.594	-0.109	8.718	1.7490	0.3002	0.2505
	(0.014)	(0.010)	(0.015)	(0.186)	(0.0013)	(3.92E-05)	
May	0.233	0.570	-0.109	8.848	1.6064	0.2864	0.2068
	(0.013)	(0.010)	(0.015)	(0.190)	(0.0010)	(2.81E-05)	
Jun	0.183	0.544	-0.134	4.071	1.4531	0.2475	0.1586
	(0.011)	(0.008)	(0.015)	(0.272)	(0.0007)	(2.86E-05)	
July	0.305	0.610	-0.116	7.846	1.8302	0.3302	0.2694
	(0.016)	(0.017)	(0.015)	(0.109)	(0.0013)	(3.43E-05)	
August	0.197	0.547	-0.069	3.868	1.4882	0.2598	0.1807
	(0.011)	(0.009)	(0.016)	(0.276)	(0.0007)	(3.43E-05)	
September	0.173	0.492	0.377	1.876	1.3314	0.2583	0.2395
	(0.014)	(0.017)	(0.023)	(0.438)	(0.0015)	(0.0002)	

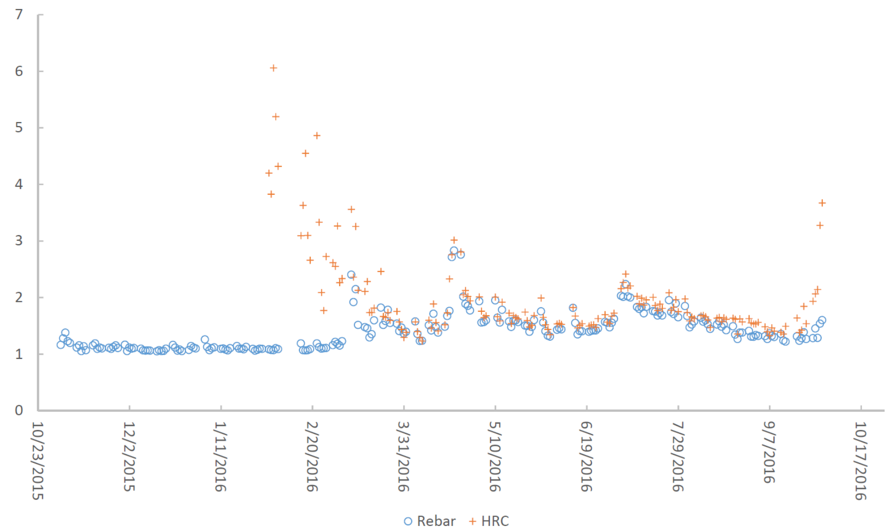
This table report the monthly average of daily GMM parameter estimates of the MRR model for the rebar contract with October 2016 expiry. GMM standard errors are in the parentheses.

Table 3.2: The GMM model parameter and trading cost estimates of the HRC futures contract expired 10/2016

	θ	ϕ	ρ	J-test	S^{MRR}	r	Price Impact
January	1.023	0.838	0.794	0.598	3.889	0.640	1.851
	(0.447)	(0.592)	(0.054)	(0.560)	(0.733)	(0.155)	
February	0.624	0.770	0.775	0.394	2.789	0.463	1.114
	(0.188)	(0.295)	(0.035)	(0.655)	(0.383)	(0.033)	
March	0.461	0.585	0.608	1.168	0.463	0.441	0.744
	(0.054)	(0.073)	(0.024)	(0.444)	(0.021)	(0.001)	
April	0.343	0.582	0.188	3.932	1.851	0.361	0.384
	(0.019)	(0.005)	(0.019)	(0.295)	(0.003)	(0.0001)	
May	0.286	0.566	0.090	3.004	1.705	0.334	0.3111
	(0.015)	(0.004)	(0.019)	(0.343)	(0.002)	(4.34E-05)	
Jun	0.232	0.542	0.136	1.626	1.549	0.298	0.262
	(0.014)	(0.002)	(0.020)	(0.438)	(0.001)	(5.40E-05)	
July	0.352	0.632	0.031	3.657	1.969	0.356	0.361
	(0.018)	(0.003)	(0.018)	(0.229)	(0.002)	(4.62E-05)	
August	0.256	0.554	0.164	1.665	1.620	0.315	0.296
	(0.015)	(0.002)	(0.021)	(0.380)	(0.001)	(4.92E-05)	
September	0.333	0.549	0.561	0.754	1.764	0.369	0.538
	(0.052)	(0.064)	(0.026)	(0.527)	(0.038)	(0.002)	

This table report the monthly average of daily GMM parameter estimates of the MRR model for the HRC contract with October 2016 expiry. GMM standard errors are in the parentheses.

Figure 3.1: Monthly average of daily implied bis-ask spreads estimates of rebar and HRC futures contracts with October 2016-2017 expiries.



The implied bid-ask spreads of the HRC contract exhibits a normal U-shaped pattern over the lives of these contracts. This reflects the illiquidity at the beginning and the end of the HRC contract. On the other hand, the implied bid-ask spread of the rebar contract depicts an inverse U-shape which implies the higher adverse selection costs. The higher adverse selection cost implies the presence of relatively more informed traders. Hence, market makers set relatively higher spreads to compensate for losses caused by adverse selection. It is noticeable that the market making cost ϕ is a dominating factor in determining the bid-ask spread of the rebar contract comparing to the equal contribution of transaction cost and information cost to the bid-ask spread of the HRC contract.

3.5 Effects and mechanism of interventions

In response to a surge in speculative trading activity, the SHFE started to roll out a series of intervention policies such as raising fees and margin requirements, limiting trading positions, and tightening rules. Those interventions aim to restrain speculation and curb volatility risk. However, government interventions were shown to have unintended consequences in different stock and foreign exchange markets. While previous government interventions in financial markets, with exception of foreign exchange market, often involved with a single policy for a fixed period of time such as the short-sale ban or price limit in stock markets. China interventions in the futures market employed multiple different policies and were carried out actively to shape the market. Due to the uncertainty nature of the intervention, they may have a broader impact on the trading activities and the quality of the market. In this section, we will investigate the impacts and mechanisms of those interventions on trading activities such as trading volume, position turnover rate, and market qualities such as volatility and trading cost.

3.5.1 Effects on trading activities and market quality

To investigate whether the market quality differs from normal on the days of intervention announcements, we regress the trading activities and market quality factors on the intervention dummy variable. The examined trading activities are trading volume and position tenure rate, and the studied market qualities include volatility, price impact, and implied bid-ask spread.

$$Y_t = \alpha + \beta Intervention_t + \varepsilon_t \tag{3.10}$$

where Y_t is the trading activity or market quality factors at time t, and $Intervention_t = 1$ for the days of the intervention announcements and zero otherwise. These intervention announcements are documented based on the official news and announcements on SHFE website. All of these interventions targeted only traders of the rebar contract except for the margin hike announcement in early March was aimed at both rebar and HRC contract. The estimates of intervention impacts are presented in the table 3.3

Impacts on trading activities

China commodity market rallied rapidly since the beginning of 2016 with the turn over of a rebar contract exceed the total traded value on the Shanghai Stock Exchange and its

Table 3.3: Effects of interventions

	Rebar	HRC
Volume	0.534**	-0.201
	(0.168)	(0.249)
PTR	-0.065**	-0.010
	(0.021)	(0.095)
Volatility	4.636***	4.401**
	(1.217)	(1.442)
Price Impact	0.076***	0.108**
	(0.016)	(0.041)
S	0.262***	0.293***
	(0.056)	(0.077)

This table presents the β estimates of the intervention effects from model 3.10. The estimates are on the top rows, the standard errors are in the parentheses on the bottom rows. The '***' represents the siginificant level at the 0.1%, '**' at the 1% '*' at the 5%, and '.' at the 10%.

total trading volume has surpassed the WTI contracts. In response to the wild movement of the market, China government rushed into action to tame the speculation activities and to prevent the market meltdown. The actions taken by Chinese government included raising fees and trading margin to make trading more costly, and imposing trading limit, position quota, and tightening rules to prevent or to stop traders from engaging in speculation. However, those interventions have failed to achieve their goals of curbing trading activities and restraining speculation. table 3.3 shows that interventions have increased the trading volume and reduce the position turnover rate of the rebar while have no impact on the HRC contract.

The trading volume of the rebar increased when the interventions were announced. This behavior did not appear on the HRC contract which was not a target of the intervention. Boehmer et al. (2013) also observed the similarity of abnormal trading volume in the banned stock in the New York Stock Exchange during the 2008 short-sale ban. While the increase in trading volume of the banned stock in the NYSE was considered to be the effect of bailout news, the surge in the rebar trading volume could be attributed to the speculation of traders on the intervention of the government.

The decrease of the position tenure rate correspondingly to the time of intervention announcements provided the evidence of speculation. This irregularity also was not visible in the HRC contract. The position tenure rate measures the likelihood of trader holding on their positions. The poistion tenure rate is the ratio of the open interest and the trading volume. Open interest measures the flow of money into the futures market. Increasing open interest represents new money coming into the market while decreasing open interest indicates money flowing out of the market. A lower position turnover rate, in this case, suggested that traders were less likely to hold on to their position. The fast turnover of the trading position is a sign of increased speculation and growing inventory risk aversion. It may also explain the negative autocorrelation in order flow of the rebar contract.

Impacts on trading activities and market quality

Government interventions were reported to deteriorate the market quality. It has been documented that government interventions induce the volatility in the market (Boehmer et al., 2013), elevate price impact of trades (Boehmer et al., 2013; Brogaard et al., 2017), increase bid-ask spread (Naranjo and Nimalendran, 2000; Boehmer et al., 2013; Brogaard et al., 2017), and worsen the information efficiency of asset prices (Pasquariello, 2017). table 3.3 confirms the exists of those impacts of government interventions on the futures market.

The volatility of both the rebar and the HRC were seen to rise when the interventions were revealed (see table 3.3). Government interventions not only injected the uncertainty into the intervened market but also instigate the fear of uncertainty into the uninterfered market. By setting different position limit and trading quotas for different types of traders, or selectively suspending trader accounts, the government gets into the business of deciding winners and losers. This undoubtedly causes uncertainty in the market. Due to the fear of unexpected interventions, traders may avoid to hold inventory or try to look for an alternative asset to invest. Therefore, we see the negative autocorrelation of order flow in the rebar contract and spilled-over volatility in the HRC contract.

The price impacts of trades were also shown to increase with the interventions. Price impact is the consequence of the market activity that is often overlooked in previous studies. Boehmer et al. (2013) study was the only one looked at the consequence of price impact of the short-sell ban. They found the effect of the ban on the price impact of both the banned and the non-banned group. However, the price impact of the ban group was found to increase more than two times the price impact of the non-ban group. Price impact measures the liquidity of the market due to the imbalance in supply and demand. This imbalance is caused by a large buy (sell) order or informed trading. In this case, the increase in price impact was most likely caused by the informed trading since the autocorrelation of rebar is negative.

The implied bid-ask spreads of both rebar and HRC contracts show similar behavior. Both of the rebar and HRC spreads widened when the interventions were announced. The implied bid-ask spread of the two contracts are seen to rise and fall together during the intervention period from the beginning of March to the end of August (see figure 3.1). The stronger comovement of asset prices could mean the weaker connections between them and their fundamentals.

The government interventions in fact not only worsen market quality but also diminish the informativeness of asset prices. The intervention introduces noises into asset price which in turn attract speculation of investors by diverting their attention away from asset fundamentals Brunnermeier et al. (2017). Consequently, market participants will have less incentive to acquire fundamental information, thus leading to less informative asset prices. The rolling Chow test was used to examine the links between the futures contracts and their fundamentals, i.e., the spot prices on Shanghai Metal Market.

$$F_t = \alpha + D_t + S_t + \varepsilon_t$$

where F_t is daily settlement prices of rebar and HRC futures contracts, S_t is the spot price, and D_t is an dummy variable determining the break point. The rolling Chow tests confirmed structural changes in the relationships of rebar and HRC with their spot prices respectively. Both of the structural breaks were dated 3/4/2016, a couple days before the interventions were initiated. The cointegration tests were employed to further examine the relationships of these contracts and their fundamentals.

Table 3.4 shows that both the rebar and the HRC comove with their spot price before the government intervenes in the market. However, those relationships ceased to exist when the

Table 3.4: Cointegration tests between futures contracts and their spot prices

		Rebar	HRC
Before 3/4/16	r <= 1	3.00	5.16
	r = 0	22.59**	20.16**
After 3/4/16	r <= 1	4.42	3.07
	r = 0	14.02	9.95

'***' Indicates that the null hypothesis of no cointegration can be rejected at the 1% level, '**' the 5% level, '*' the 10% level.

government started to interfere. Put in other words, the futures contracts stopped to reflect their fundamentals since the government meddled in the market. This intervention consequence is particularly pronounced in the foreign exchange market. Pasquariello (2017) showed that government intervention in a money market may induce violations of the law of one price in other, arbitrage-related markets.

3.5.2 *Mechanism of the interventions*

Understand the mechanism of the intervention can provide a great insight into the government's ability to change the outcome and would help guide the government's actions in the future. To study the independence relationship among the market variables and interventions, we proposed the used of Bayesian networks. The advantages equation (3.10) the Bayesian networks are that they address the latent factors ignored in the Granger network proposed by Billio et al. (2012) and reflect the way that investors learn in the interfered environment (Payzan-LeNestour and Bossaerts, 2015). In addition, the Bayesian network framework allows for updating of the probability distributions as new information becomes available. This capability of updating is particularly advantageous when the information the analysis of a system based on is evolving.

A Bayesian network is a probabilistic graphical model that represent a set of variables and their conditional dependencies via a directed acyclic graph (DAG) $\mathscr{G} = (\mathbf{V}, A)$ in which each node (vertex) $v_i \in \mathbf{V}$ corresponds to a random variable X_i and the arcs $a_{ij} \in A$ represents the directed dependencies between these variables. The conditional independence relationships among the variables in the model are expressed by the local probability distributions of X_i condition on its set of parents, Π_{X_i}, which can be factorized from a global probability distribution of $\mathbf{X}$.

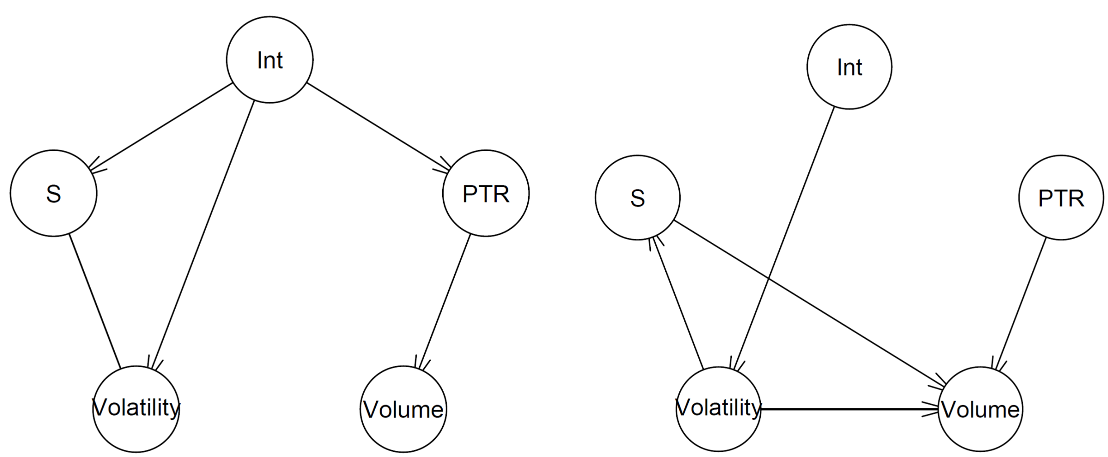
$$\mathrm{P}(X) = \prod_{i=1}^{n} \mathrm{P}(X_i \mid \Pi_{X_i})$$

If X_i has no parents, its local probability distribution is said to be unconditional, otherwise it is conditional. Nodes without parents are roots (independent) nodes and are defined by their marginal probability distributions. If the variable represented by a node is observed, then the node is said to be an evidence node, otherwise the node is said to be hidden or latent.

The task of fitting a Bayesian network is generally implemented in two steps. The first step is called structure learning which find the DAG that encodes the conditional independencies present in the data. The second step is called parameter learning which deal with the estimation of the parameters of the global distribution. Since the graph structure is known from the previous step, this can be done efficiently by estimating the parameters of the local distributions.

Figure 3.2: Intervention mechanism

(a) Rebar (b) HRC



The figure 3.2 portrays the mechanism of government intervention through the conditional interdependence network of intervention and different market factors and trading activities. The Bayesian network here is estimated using constraint based approach. The constraint based approach sequentially checks conditional independence relations among all variables by statistical testing the assumption that graphical separation and probabilistic independence imply each other. Thus, it is easy to verify the structure learned by the Bayesian network by adding all other market variables to equation (3.10) and check for the significance of their correlations.

Table 3.5: Mechanism of interventions

		c	Intervention	Volume	PTR	Volatility	S
Rebar	Volume	16.399***	0.068	NA	-2.670***	-0.013	0.278
		(0.395)	(0.071)		(0.112)	(0.014)	(0.293)
	PTR	5.346***	-0.008	-0.308***	NA	9.36e-6	-0.064
		(0.197)	(0.024)	(0.013)		(0.005)	(0.100)
	Volatility	-14.697	0.455	-0.560	0.003	NA	19.265***
		(9.840)	(0.456)	(0.583)	(1.722)		(0.729)
	S	0.876	0.008	0.026	-0.053	0.044***	NA
		(0.469)	(0.022)	(0.028)	(0.082)	(0.002)	
HRC	Volume	15.450***	-0.215	NA	-1.475***	0.064***	-1.421***
		(0.332)	(0.147)		(0.139)	(0.016)	(0.251)
	PTR	5.108***	-0.081	-0.326***	NA	-0.015	-0.064
		(0.493)	(0.069)	(0.031)		(0.008)	(0.132)
	Volatility	-33.447***	0.784	1.727***	-1.811	NA	12.840***
		(6.792)	(0.763)	(0.441)	(0.982)		(0.882)
	S	3.135***	0.044	-0.146***	-0.029	0.049	NA
		(0.364)	(0.047)	(0.026)	(0.062)	(0.003)	

The '***' represents the significant level at 0.1%, '**' at 1%, '*' at 5%, and '.' at 10%.

Table 3.5 confirms the structure of the Bayesian networks. We see that volatility and spread of the rebar are the only are the only significant variable in the estimate of each other. The similar statistical significance is also observed from the estimates of the rebar trading volume and PTR. Those explain the connection between spread and volatility, and trading volume and PTR as well as the separation among these two groups. The intervention effects disappears in the estimates suggests that intervention may have an indirect effect on those factors through the significant variable(s). For the HRC contract, the significance of trading volume, volatility and bid-ask spread confirms the connection of those three factors in the graph. Trading volume of HRC is the only significant factor of PTR which explain the link of PTR to volume and the separation of PTR with the other factors. There are possibilities that interventions have indirect effects on these trading and market quality factors since the intervention effects become insignificant when other factors are considered.

Bayesian network reveals the confounding effects and the interaction directions of the market factors under government intervention, which could not be recognized under simple regression. In the rebar contract, there is no direct effect of intervention on the trading volume as suggested in Table 3.3. Intervention inject the uncertainty into the market. To avoid mitigate that uncertainty risk, investors avoid to hold on to their position. To keep their PTR low, investors need to buy and sell more frequently which result in higher trading volume. This behavior is also observed in the HRC network. However, the low PTR could be the consequence of speculation since there is no direct effect of interventions on the PTR. The Bayesian network also indicates that there is no direct impact of interventions on bid-ask spread as suggested in table 3.3. Government intervention in the rebar market induced speculation in the HRC market, which impacts the volatility of the market. Higher volatility will effects the trading cost by widening bid-ask spread. Higher volatility and trading cost will further reinforce the speculation resulting in higher trading volume.

Another evidence of speculations on the government actions is the increasing comovement between these two contracts. Government interventions introduce noises into the market which attract speculation of short-term investors. Consequently, market participants would have less incentive to acquire fundamental information which led to less informative asset prices and stronger comovement across assets. This assertion can be tested empirically by looking at the connection between the intervention and the comovement of the two contracts. To investigate whether comovements of the rebar and HRC contracts on the normal days differ from the day of intervention announcements, we regression the intervention, 1-day lag and 1-day ahead of the intervention on the cointegration factor using the logistic model

$$\text{logit}\left(Coint_t\right) = \alpha + \beta_1 Intervention_{t-1} + \beta_2 Intervention_t + \beta_3 Intervention_{t+1} \tag{3.11}$$

where $Coint_t = 1$ if the two futures contracts are cointegrated at day t, and zero otherwise. The cointegration test is performed on the 1-minute interval data using Johansen (1988) trace test.

Table 3.6: Impacts of intervetions on the covmovement among assets

	α	$Intervention_{t-1}$	$Intervention_t$	$Intervention_{t+1}$
Coint	0.205***	0.178.	-0.040	0.178.
	(0.053)	(0.094)	(0.095)	(0.094)

This table reports estimates of 3.11. The dependent variable is the logit function of the vector indicating the cointegration between rebar and HRC. Standard errors are in parentheses. '***' indicates significance at 0.1%, '**' at 1%, '*' at 5%, and '.' at 10% level.

Table 3.6 shows that the probability that rebar and HRC comove increases significantly when intervention announcements are published. The probability that two contracts are conintegrated increases 9 percent from 0.55 when there is no intervention announcement to 0.64 when there are intervention announcements in both the next and the last periods. Traders focus on speculation of the noise in government policies leads to stronger comovement across assets and less informative asset price. As the result, the information efficiency of asset prices decline as shown in table 3.4.

The government interventions introduce noise into the equilibrium asset price. In order to reduce volatility and the price impact of noise traders, the government may want to intervene intensively in the market. As the result, the government noise factor becomes sufficiently dominant in the asset price and investors will focus on the speculation of the government's policies. Chinese traders not only allocate their attention to news about government policies but also actively seek for that information from official sources. Big Chinese financial institutions and state-backed speculators rely on their "public relation experts" to scour for information. "If you ask any Chinese investor whether they think a chairman or executive of a company is trading in their own stock, nine out of 10 would expect that to be the case just as they would expect a government official to be taking bribes," says Fraser Howie, co-author of Red Capitalism. Everyone appears to trade based on tips from contacts who claim to have insider information. Senior regulatory officials admit that government officials who have access to insider information through their duties and their relatives are some of the worst offenders.[5]

Here we will investigate whether traders know in advance the information regarding government's interventions. Leaks give traders an opportunity to anticipate the market reaction and to take profitable trading positions. Hence, we would expect to see abnormal trading activities right before official announcements. To examine whether there is a leak of insider information, we will test the abilities of trading activities to predict the probability of government intervention using the following logit model

$$\operatorname{logit}(Intervention_t) = \alpha + \beta_1 \ln(Volume_{t-1}) + \beta_2 \ln(OI_{t-1}) \tag{3.12}$$

Table 3.7 that the abnormal trading activity a day before intervention announcement could predict the incoming intervention. Higher trading volume and lower open interest hint at a higher chance of intervention. Investors with inside information will try to get out of the market before the government has an action. Thus, the flow of money out of the market will be indicated by a high trading volume accompanied by a low open interest.

Table 3.7: Informed trading

	α	$Volume_{t-1}$	OI_{t-1}
Rebar	6.398	1.928**	-2.585*
	(13.175)	(0.637)	(1.157)
HRC	6.391.	0.254	-0.757*
	(3.381)	(0.213)	(0.336)

This table reports estimates of equation (3.12). The dependent variable is the logit function of the intervention. Standard errors are in parentheses. '***' indicates significance at 0.1%, '**' at 1%, '*' at 5%, and '.' at 10% level.

[5] https://www.ft.com/tour. https://www.ft.com/content/751a82ca-f7f4-11df-8d91-00144feab49a

3.6 Conclusion

The intervention of China government into the futures market, especially the steel market, provides a natural experiment of the effects of the intervention policies that are rarely seen in other market. Since the two contracts share the same fundamental, they provide a unique opportunity to study the difference of the intervention impacts between intervened and non-intervened contracts. We found that the interventions have worsened the market quality of both the rebar and the HRC contracts but only impacted trading activity of the rebar contract. Volatility, price impact, and bid-ask spread of both contracts went up at the day interventions were published. However, only the trading volume of the intervened contract, the rebar contract, increased when the interventions are announced. Investors traded more but they avoid to hold on to their position which lead to lower position tenure rate at those days. Volatility is the key mechanism of intervention that impact the market quality and trading activity. Government intervention create an uncertain environment which lead to the risk of holding inventory. Consequently, investors were trading more and were less likely to hold on to their position. Higher volatility also drove the trading cost up and made bid-ask spread wider. Moreover, intervention attract short-term speculators to bet on government actions rather than focus on the fundamentals. As the results, the contract prices become less informative and the comovement between two contracts gets stronger. The connections between the two contracts and their spot price were disrupted days before interventions were rolled out; and they were more likely became cointegrate when the intervention were announced.

Moreover, there is evidence of informed traders in the market. Trading activities such as trading volume and open interest could predict the incoming government intervention. Higher trading volume and lower open interest on the day before an intervention is announced indicates that money is flowing out of the market before government acts. Some traders must be tipped off so they could act ahead of the government move. Leaked information from government officials is a major concern and an evidence that China futures market is still not a developed and reliable market.

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