Commodity Spot Prices:

An Exploratory Assessment of Market–Structure and Forward–Trading Effects[1]

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Abstract:

In this paper, we assess how the characteristics of product and forward markets affect commodity–price distributions. In particular, we assess the levels and volatilities (means and standard deviations) of the spot prices of the six commodities that were traded on the London Metal Exchange in the 1990s. The theories that we examine can be grouped into four classes. The first considers how product–market structure and forward–market trading jointly affect the spot–market game, the second explores the links between product–market structure and spot–price stability, the third assesses whether forward trading destabilizes spot prices, and the last relates the arrival of new information to price volatility and the volume of trade. We find support for traditional market–structure models of the price level but not of price stability. In addition, increased forward trading is associated with lower prices. Finally, although we find a positive relationship between increased trading and price instability, the link appears to be indirect via a common causal factor.

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1 Introduction

The behavior of commodity prices, an issue that has received considerable attention from academics, is also a major concern for producers and consumers. Indeed, many producer countries depend on revenue from commodity exports to support their industrialization, whereas consumer countries depend on imports of raw materials to fuel their growth. Moreover, one has only to look at the history of the formation of stockpiles and other schemes that attempt to stabilize prices, as well as the rise and fall of cartels and producer organizations that attempt to increase prices, to realize that the stakes are high.[2] It is therefore not surprising that economists have devised models that explain how commodity–price distributions — means and variances — are determined. Researchers from different subdisciplines, however, see price determination from very different points of view.

Most commodity markets are distinguished by the fact that there is a spot or cash market in which the physical product is sold as well as a forward market in which contracts for future delivery of the product are sold.[3] In this paper, we assess how the characteristics of the two markets affect spot–price formation. The theories that we examine can be grouped into four broad classes. The first considers how product–market structure and forward–market trading interact to affect the spot–market game, the second explores the links between product–market structure and spot–price stability, the third assesses whether forward trading destabilizes spot prices, and the last relates the arrival of new information to price volatility and the volume of trade. There is clearly an abundance of theories that link the two markets. Empirical assessment of whether those theories can explain spot–price distributions, however, is more rare.

We evaluate the models from the four strands of the literature in an integrated framework. However, because there are many theories, the approach that we take is descriptive rather than structural. In other words, we seek to determine which models are consistent with the data and which are not. Furthermore, we ask if there are empirical regularities that cannot be explained by any of the theories. Our research is therefore an exploratory assessment of the links between industrial and financial markets. Moreover, *any* significant finding, regardless of sign, is evidence of

[2] Perhaps the best example of an organization that attempted to influence the level and stability of the price of a commodity in recent years is the International Tin Council (see, e.g., Anderson and Gilbert 1988).

[3] We make no distinction between futures and forward markets. The London Metal Exchange has features of both. Furthermore, whether or not delivery actually occurs or whether the contract is bought or sold back before falling due is not important for our purposes. We simply wish to distinguish between markets for contracts and markets in which purchase is immediate.

a link. In other words, it is an indication that forward trading has real effects.

The markets that we study are for the six metals that were traded on the London Metal Exchange (LME) during the 1990s: aluminum, copper, lead, nickel, tin, and zinc. By considering multiple commodities, we obtain cross–sectional as well as time–series variation in both product–market structure and financial–market liquidity. By limiting attention to a set of related commodities, however, we are able to hold the financial–market microstructure and the set of contracts under which the commodities were traded constant and can thus focus on the variables of interest. With this task in mind, we assembled a panel of data that includes both financial and real variables. This panel allows us to assess the theoretical predictions concerning both time–series and cross–sectional variation in price distributions.

Our data come from two sources: financial variables such as turnover and open interest were obtained from the LME, whereas real data on the activities of firms were provided by the Raw Materials Group. We use the former to characterize the liquidity and depth of the forward market, whereas we use the latter to construct concentration indices and other indicators of the structure of the product market.

The first data source is fairly standard. The second, however, is more unusual. Indeed, most data–collection agencies publish commodity statistics by geographic region, and those data contain no information on market structure. The Raw Materials Group, in contrast, keeps track of the activities of mining companies. In particular, it tracks mergers and other changes in the complex linkages among mining and refining firms and is consequently a unique source of data on who owns and controls whom.

To anticipate, we find considerable support for traditional market–structure models of spot–price levels but not of price stability. In addition, we find that increased forward trading reduces the effect of concentration on price levels. Finally, although we find a positive relationship between forward trading and spot–price instability, there is no evidence of a direct link. Instead, the relationship appears to be due to a common causal factor such as the arrival of new information.

The organization of the paper is as follows. In the next section, we discuss the theories that form the basis of our empirical tests as well as previous tests of those theories. Section 3 describes the London Metal Exchange, section 4 discusses the data, section 5 develops the empirical model, and section 6 presents the empirical results. Finally, section 7 concludes.

2 The Models

In this section, we discuss industrial–organization (IO) models of commodity spot prices, whose predictions are principally concerned with variations in product–market structure, and other economic and financial models, whose predictions are principally concerned with variations in forward–market liquidity.

2.1 Product–Market Structure

2.1.1 The Price Level

Many IO models predict that, at least when products are homogeneous as is the case with commodities, the price level (relative to marginal cost) is determined to a large extent by the structure of the industry. Moreover, industry structure is often summarized by some notion of the number and size distribution of the firms in the market. Nevertheless, the sensitivity of prices to industry structure depends very much on the game that the firms are assumed to play.

To illustrate, consider the simple Cournot and Bertrand models of spot–market trading. In the Cournot model, firms play a quantity game and price rises with industry concentration, whereas in the Bertrand model, firms play a price game and marginal–cost pricing prevails as long as the market is not monopolized.

More recently, economists have incorporated forward–market trading into spot–market games.[4] For example, Allaz (1992) shows that, in a two-period Cournot game with forward trading in the first period and spot trading in the second, the introduction of a forward market causes the spot price to fall from the Cournot level to one that is closer to Bertrand. The reason is simple: forward trading reduces the number of units that are sold in the spot market, which increases the marginal revenue from each unit sold and causes firms to increase output. Nevertheless, although the dependence of the price level on industry concentration is weakened in this model, the link is still positive.

Allaz and Villa (1993) modify the two–period model to encompass multiple periods of forward trading followed by a single period of spot trading. They show that as the number of periods of forward trading increases, or equivalently as the period between trades falls, price approaches marginal cost. Given that trading in most forward markets is continuous, their model, like the Bertrand model, predicts that marginal–cost pricing will prevail regardless of market structure. In other words, the price–level/market–structure link is broken.

[4] For a survey of the earlier literature on this subject, see Anderson (1991).

Finally, Thille and Slade (2000) question why the spot market meets just once in the Allaz and Villa model. In particular they show that, if the inability of firms to change output is due to adjustment costs, output is lower and prices are higher than in the two–stage game, contrary to the Allaz and Villa finding.[5]

These dynamic models rely on the assumption that participants can enter into binding and observable commitments. Unfortunately, this is rarely the case, since contracts for future delivery can be sold. However, it is still of interest to test whether the volume of forward trading affects the level of spot–prices.[6]

2.1.2 The Volatility of Prices

There are many informal models that suggest that prices should be more stable in imperfectly competitive markets. For example, firms might refrain from changing prices in response to cost and demand shocks for fear of triggering price wars, or kinked–demand curves might lead to ranges of marginal–cost changes that are not met with price changes. In addition to these informal stories, there are a number of formal links between market structure and price stability.

To illustrate, Newbery (1984) contrasts the degree of price stabilization (via storage) that firms undertake in perfectly competitive markets with that undertaken by a dominant firm. When choosing the amount to store, firms set the marginal cost of storage equal to the marginal benefit. The implications for price stability arise because perfectly competitive firms' marginal benefits are based on price, whereas a dominant firm's benefit is based on marginal revenue. Newbery shows that, when demand is linear, storage and thus price stability increases with a dominant firm's market share.[7]

In a second model, Newbery (1990) introduces the possibility of forward trading. He notes that, since forward markets reduce risk, they encourage fringe firms to supply more output and thus reduce the spot price. A dominant firm or cartel might therefore want to undertake excessive storage or price stabilization in order to undermine the forward market.

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[5] The above games all have a Markov structure in which actions depend only on a payoff–relevant state. However, the price/concentration relationship persists in (non–Markovian) repeated games. For example, when a cartel is supported by trigger–price strategies, as the number of firms increases, the temptation to cheat becomes stronger. Indeed, the gains from defection increase, the punishment becomes less severe, and tacitly collusive agreements become harder to maintain (see, e.g., Tirole 1988, pp. 247).

[6] The models that link capital–market structure and product–market competition (e.g., Brander and Lewis 1986), which have been tested by Chevalier (1995), suffer from the same problem.

[7] More generally, if storage and arbitrage can also be undertaken by competitive intermediaries, the presence of imperfect competition tends to reduce price instability regardless of the shape of the demand curve.

Finally, in a real–options context, a dominant firm has an incentive to control upward price spikes. Indeed, such spikes can lead potential entrants to exercise their investment options, and those entry decisions are not easily reversible. With all three models, therefore, market concentration and price instability are negatively related.

2.1.3 The Predictions and Tests of Those Predictions

The testable predictions of the market–structure models of commodity–price determination are summarized in Table 1. To reiterate, those models predict that prices should not be lower or less stable in more concentrated industries.

On the empirical side, there is a large literature that assesses the relationship between product–market concentration and firm profitability (see Schmalensee 1989 for a survey). Those studies, which tend to find a positive but weak link between the two, do not assess how forward–market trading affects the relationship. In addition, if profits are higher in concentrated industries, it could be due to market power that allows firms to raise prices or to economies of scale that allow them to lower costs, and it is difficult to disentangle the two effects. Since we assess how market structure is related to price levels conditional on costs, we do not confound the two effects.

A few empirical researchers have also assessed the relationship between market structure and price stability (see, e.g., Carlton 1986, Slade 1991, and Domberger and Fiebig 1993). Those studies tend to find that price variability is lower in concentrated industries.

2.2 Forward–Market Liquidity

2.2.1 The Price Level

There are a number of ways in which the intensity of activity in the financial market can affect the spot–price level. For example, forward markets allow risk–averse participants to hedge exposure to risk. When hedging is undertaken by producers, the supply of the spot commodity is affected, whereas when it is undertaken by consumers, demand is affected.[8] Since hedging changes both supply and demand, the direction of the net effect is ambiguous. Nevertheless, if producer hedging is more important than consumer hedging, increased trading will lower prices.

Furthermore, in the absence of forward markets, commodity trading can be very fragmented. Forward markets, however, concentrate trading in one location and reduce information and other transactions costs, which can also lower prices.

[8] Newbery and Stiglitz (1981) show that, for example, in an uncertain environment risk-averse producers increase supply when a forward market is added, and price falls as a consequence.

Finally, the Allaz (1992) and Allaz and Villa (1993) models yield predictions concerning the effects of financial–market liquidity as well as product–market structure on the price level. Indeed, an increase in trading can mean that a smaller fraction of each firm's output is affected by the spot–market game. When that is the case, marginal revenue moves closer to price, and price falls as a consequence.

2.2.2 The Volatility of Prices

Destabilizing Speculation

The introduction of a forward market serves two important functions, it reduces risk and it increases the amount of information that flows into the market. It is therefore not surprising that economists have focused on those two functions in attempting to discover whether forward–market trading destabilizes spot–market prices.[9]

Many market participants believe that forward trading is destabilizing. Nevertheless, most of the early economic models that examined the issue concluded that the opposite was true. For example, Turnovsky (1979) and Turnovsky and Campbell (1985) focus on the risk–reduction effect and note that, since forward markets reduce the price risk of holding inventories, larger inventories are held and prices tend to stabilize as a consequence. In their model, inventory holding is not stochastic. Kawai (1983), however, shows that when storage is subject to shocks, increased storage can destabilize prices. Finally, Newbery (1987) builds a model in which risk reduction encourages producers to undertake more risky investment projects, and risky investment destabilizes spot prices. Furthermore, he points out that, in general, forward markets encourage risk taking and that the effect on the spot price depends on whether the risky activity tends to be stabilizing or destabilizing.

Early models of the information effect also led to the conclusion that the introduction of forward markets stabilizes spot prices. For example, both Cox (1976) and Danthine (1978) note that speculators arrive with new information and show that better information lowers spot–price volatility. However, Stein (1987) points out that a change in the information content of prices inflicts an externality on traders, and that this externality can be either positive or negative. In other words, even when all traders are rational, there can be a misinformation effect that can destabilize prices.

Exogenous Information Arrival

[9] Researchers often seek to determine how the introduction of a forward market affects the spot–market price. In other words, they examine an all–or–nothing situation in which there is either a forward market or there is not. However, it is also interesting to ask whether more speculation is better than less. In our empirical work, we address the second question. However, most of the arguments that are advanced in the all–or–nothing literature extend easily to the more–or–less issue.

With the informational models described above, there is a direct causal link between trading volume and price stability. However, it is also possible that volume and volatility are affected by a common–causal factor and that there is no direct connection between the two. This will be the case, for example, when the exogenous arrival of information causes both trading volume and price volatility to increase.[10] Furthermore, in that situation, the two variables will be positively correlated.[11]

2.2.3 The Predictions and Tests of Those Predictions

The testable predictions of the theoretical models of forward trading are summarized in Table 2. To reiterate, both informal stories and formal models lead one to expect lower prices in markets in which trading is intense. As to price stability, the predictions from the destabilizing–speculation literature are mixed. Models with exogenous information arrival, in contrast, predict that prices will be more volatile in markets with intense trading.

On the empirical side, the relationship between price levels and forward trading has received little attention. Nevertheless, Williams (2001) documents a negative relationship between open interest (one of our measures of trading activity) and price for several commodities.

A number of empirical researchers have assessed the destabilizing–speculation issue. In particular, they have examined how the introduction of a forward market affects the spot price, and, like the theoretical predictions, the empirical results are mixed. For example, Cox (1976) finds that in many markets forward trading is stabilizing, whereas Figlewski (1981) and Simpson and Ireland (1985) conclude that the opposite is true.

To our knowledge, no one has assessed the effect of exogenous information arrival on spot prices.[12]

[10] Examples of exogenous information include rumors of political disruptions in producer countries, which could lead consumers to increase their inventories, thereby increasing the spot price, and to take long positions in the forward market.

[11] The distinction between exogenous and endogenous information arrival is often made in the finance literature that seeks to explain the distribution of futures prices. To illustrate, with exogenous–information models such as the 'Mixture–of–Distributions' (e.g., Clark 1973, Epps and Epps 1976), the variance of returns in a period is positively related to the volume of trade in that period. However, there is no causal link. Instead, both are determined by the arrival of new information. With models in which information acquisition is endogenous and traders have timing discretion (e.g., Admati and Pfleiderer 1988), information arrival also generates trade and volatility. However, there is also a direct link between the two variables, since increased volatility induces more trading, which in turn affects information acquisition.

[12] There is, however, a large empirical literature that uses futures–price data to assess the Mixture–of–Distributions hypothesis, which is similar. Although there is some variation, most of those studies find a positive relationship between the two variables (see the survey by Karpoff 1987).

3 The Market and the London Metal Exchange

Commodities are homogenous products that can be sold under standard terms. In other words, buyers are usually indifferent concerning the identity of sellers. Furthermore, many agricultural commodities are produced by a very large number of sellers. For these reasons, commodity markets are often thought to be textbook examples of the perfectly competitive norm.

Some mineral commodities, however, are sold in markets with relatively few sellers, and those markets are not perfectly competitive. In particular, there are substantial economies of scale in mining and even more in refining. As a consequence, mining firms are included in lists of the world's largest. However, the markets in which they operate are also large; in fact, they are worldwide. Due to their geographic size, most mineral–commodity markets are not highly concentrated. Instead, they range from workably competitive to moderately concentrated.

There are a number of stylized facts that characterize mineral–commodity physical or product markets. First, demand is driven by economic activity and is both cyclical and inelastic. Second, production is capital intensive and can be difficult to alter in the short run. This means that, when capacity constraints don't bind, marginal cost is below average cost. When capacity constraints are tight, in contrast, supply is highly inelastic and price spikes occur. Finally, many firms operate in developing economies in which the foreign exchange that is obtained from commodity sales is very important for growth. Those firms are less likely to cut production in a downturn. The combination of these three factors causes prices to be highly unstable. In particular, the industries are characterized by periods of excess supply, in which prices are low but high–cost facilities might not shut down, as well as periods of excess demand, in which prices are high but capacity limits production. Profits are therefore also highly unstable.

In addition to similarities, each commodity market has its unique features. For example, some commodities are more homogeneous than others (copper versus nickel) and thus more conducive to trading under standardized contracts.[13] Moreover, the formation of cartels and attempts to corner the market are more common in some markets than others. For example, in addition to the tin crisis in the 1980s (see footnote 2), there were attempts to corner the silver market in 1979-80 and the copper market in the mid 1990s. The former resulted in an extreme but temporary price spike,[14] whereas the latter resulted in only moderate price increases. Nevertheless,

[13] This is perhaps one reason why nickel trading began so late.

[14] This spike, however, is outside the period of our data. For a different interpretation of the spike, see Fama and French (1988).

in spite of clear differences across markets, we feel that the similarities are sufficient to warrant treating our sample as a panel.

The commodities that we examine are the six metals that were traded on the London Metal Exchange (LME) during the 1990s: aluminum, copper, lead, nickel, tin, and zinc.[15] The LME is by far the most important market for nonferrous metals, with an annual turnover value of about US $2,000 billion.[16]

The LME was formally established in 1877 in the wake of the industrial revolution. It flourished because it established a single marketplace with recognized times of trading and standard contracts. The number and identity of the metals that were sold has varied over time. Copper and tin have traded since the beginning,[17] lead and zinc were introduced in 1920, aluminum was introduced in 1978, and nickel started trading in 1979. Finally, a silver contract was launched in 1999.[18]

An unusual feature of LME contracts is that they are for delivery on a specific day, which means that every day is a delivery date for some contract. Furthermore, contracts are settled on the day that they are due. This practice can be contrasted with the continuous–settlement practice that is used by many other exchanges. Finally, the LME operates under a clearing–house system. The clearing house is an independent body that guarantees transactions between brokers. In particular, the house assumes one side of all trades.

In addition to providing hedging opportunities to producers and consumers, the primary functions of the LME are to establish worldwide reference prices and to enable market participants to take physical delivery. At the LME, each of the six commodities trades in turn for short (five–minute) periods of open outcry among ring–dealing members. Open outcry or ring trading takes place four times each day on the market floor. In addition, the LME operates a 24–hour market through inter–office trade. After the second floor–trading period, the LME announces a set of official prices that are used by industry members to write contracts that govern the movement of physical metal. Official prices are determined for both cash settlement and forward trading.

In spite of the fact that only a small fraction of LME contracts result in physical

[15] For more information on the LME, see their web page at www.lme.co.uk or Slade(1988).

[16] Copper and aluminum are also traded on COMEX. However, COMEX trade in aluminum was never thick, and the COMEX copper contract is dominated by the LME contract. Nevertheless, failure to consider COMEX copper trading is a limitation of our analysis. However, unless activity is very different across markets and copper–trading shares are highly unstable, it is not a serious limitation. Furthermore, differences in trading practices on COMEX (e.g., continuous settlement and limits on daily price changes) make combining volume data from the two markets unwise.

[17] Tin trading was temporarily suspended after the collapse of the International Tin Council but resumed in 1989.

[18] However, this was not the first LME silver contract.

delivery, all contracts assume delivery. For this reason, the LME has established approved warehouses around the world where large stocks of metal are held. The levels of stocks in those warehouses can be used as indicators of physical–market supply and demand conditions.

4 Data and Preliminary Data Analysis

We consider the period from January 1990 to January 1999. This interval was chosen with two criteria in mind: i) the same metals should be traded over the entire period, and ii) the terms of the contracts for those metals should not change during the period. A tin contract was reintroduced in 1989, and silver began trading again in 1999. Since there were no changes in the terms of the contracts for the other metals during that interval, those two events delimit our sample period.[19] More importantly, the detailed financial and firm data are available only from 1990 onwards.

Most of our data come from two sources. Financial data (prices, turnover, open interest, and inventories) were obtained directly from the LME and are either daily or monthly. Data on firms (output and profits) were obtained from the Raw Materials Group (RMG) and are yearly. In addition, we have monthly data on demand (industrial production) and cost (factor prices) that do not vary by commodity. All monetary variables were deflated using the OECD producer–price index (OECD 1999) and are thus in constant dollars.

An observation pertains to a specific commodity (aluminum, copper, lead, nickel, tin, or zinc) in a particular month, which results in a total of 648 observations. We chose to focus on months as a compromise between shorter–term financial variables and longer–term real variables. All variables have been normalized so that they are comparable across commodities.

Our LME variables for each commodity are constructed as follows:

Spot price (PS) is the monthly average of the daily real cash–settlement price. To ensure comparability across commodities, all prices were divided by the price of the commodity in January 1990 and multiplied by 1000. The normalized spot price (PSR) is used in the regressions.

Spot–price volatility (SIGPS) is the standard deviation of daily percentage changes in the real spot price during the month. 100 times the natural logarithm of this variable (LSIGPS) is used in the regressions.

[19] Additional contracts were introduced after 1999. There are currently nine, including various aluminum alloys. Moreover, prior to our sample period, the terms of many existing contracts changed.

Forward price (PF) is the monthly average of the daily real three–month forward price. As with spot prices, each forward–price series was divided by the price of the commodity in January 1990 and multiplied by 1000. This normalized price is denoted PFR.

Forward–price volatility (SIGPF) is the standard deviation of daily percentage changes in the real forward price during the month. 100 times the natural logarithm of this variable is denoted LSIGPF.

Turnover (TURN) is the monthly average of daily sales of futures contracts (in lots, which is the contract unit) divided by yearly Western–world production of the commodity (also in lots). This variable is multiplied by 100.

Open interest (OPEN) is the monthly average of open interest (all open forward positions in lots) divided by yearly Western–world production of the commodity. This variable is also multiplied by 100. Open–interest figures are based on the sum of all net long or all net short forward positions at the London Clearing House.

Inventories (STOCK) is the monthly average of daily LME stocks divided by yearly Western–world production of the commodity, also multiplied by 100.

PSR is our measure of the price level, whereas LSIGPS is our measure of price volatility. Both are fairly standard.[20] TURN and OPEN are our measures of trading activity or volume. Turnover, which equals the number of trades in a day, is the more usual proxy for volume. At the LME, each trade generates a new contract between the trader and the exchange or clearing house. Some of those trades, however, offset previous positions held by the traders. Open interest measures the number of trades that have not been offset. A number of researchers have attempted to distinguish between the two variables. For example, Bessembinder and Seguin (1993) note that the difference is determined by the number of day traders — traders who enter and offset positions within a trading day — and that open interest is therefore a proxy for hedging or uninformed trading. Kyle (1984), in contrast, suggests that open interest is often concentrated in the hands of a small number of traders who take large positions and might therefore behave strategically. We simply note that turnover and open interest potentially measure the activities of different sets of traders and include both measures in our analysis. Finally, STOCK measures supply/demand imbalance.

Table 3, which gives summary statistics for the LME variables, shows that there is substantial variation in all of those variables. Moreover, one can see that, on average, prices have fallen. Furthermore, daily inventories and turnover are very large — on average nearly one tenth of annual world production. The second half of Table 3

[20] Note, however, that we use daily prices to construct actual standard deviations in contrast to the approximation that is used in many financial studies (see, e.g., Schwert and Seguin 1990).

presents some statistics of the futures–market data that have been disaggregated by commodity. It is interesting to note that turnover and open interest exhibit different cross–sectional patterns. For example, the commodity with the largest turnover (copper) has only the third largest open interest.

The data on firms are more unusual. RMG publishes annual data on the production of each commodity by each firm as well as other firm variables such as accounting profits.[21] We use the data for refinery production to construct annual indices of commodity–market concentration as well as total production. Our annual product–market variables for each commodity are:

Hirschman/Herfindahl index (HHI) is the sum of the squared market shares of individual firms, multiplied by 10,000.

Four–firm concentration ratio (CR4) is the percentage of industry output that is supplied by the four largest firms in the market.

Western–world production (WWQ) is total annual output of the commodity. This variable is used as a normalization factor (see above).

Summary statistics for the RMG variables also appear in Table 3. The second half of this table shows that the tin and nickel markets are more concentrated (on average, $1000 < HHI < 1400$), whereas the other four markets are more competitive (on average, $100 < HHI < 500$). Furthermore, turnover is somewhat higher in copper, a relatively competitive industry, whereas open interest is much higher in tin and nickel, the relatively concentrated industries.

We also collected monthly data on demand and cost variables that are common to all commodities. Except where noted, those variables were found in the OECD Statistics Compendium (1999).

Industrial production (IP) is aggregate real industrial output of the OECD countries, 1990 = 100.

Energy price (ENP) is an index of real energy prices for OECD countries, 1990 = 100.

Hourly earnings (WAGE) is an index of real hourly earnings for OECD countries, 1990 = 100.

Price of mining machinery and equipment (MME) is the real US producer–price index for mining machinery and equipment, 1990 = 100, from CITYBASE.

Interest rate (INT) is the average of a number of short–term interest rates.[22] A real interest rate (RINT) was created by subtracting the rate of inflation in OECD

[21] For more information on the Raw Materials Group, see their web page at www.rmg.se.

[22] Specifically, it is the average of US 3–month certificates of deposit, Japanese 3–month certificates of deposit, French 3–month interbank–loan rate (FIBOR), German 3–month interbank–loan rate, and UK 3–month interbank–loan rate (LIBOR).

countries from the nominal average.

None of the factor–price variables is ideal. Unfortunately, it was not possible to find more disaggregated monthly cost data for such a broad geographic region. Summary statistics for the demand and supply variables are also shown in Table 3.

In order to examine time–series patterns in the data, we averaged across commodities using two weighting schemes — equal and value (revenue) weights. Figures 1 and 2 illustrate the time–series behavior of real spot–price levels and volatilities. There is clearly a downward trend in prices, whereas the volatility graphs exhibit spikes but show no obvious trend. Both turnover and open interest (not shown) increased sharply during the first half of the decade and flattened out in the second.

Figure 3 contains graphs of the Hirschman/Herfindahl index of concentration for the six commodities. The cross–sectional differences noted earlier are obvious in the figure. As to time–series patterns, most striking is the variation in concentration in the tin market. There are no obvious trends.

Finally, histograms showed that the price–level distribution is unimodal and symmetric, whereas the volatility series are skewed to the left. Taking logarithms of volatility, however, removes the skewness.

5 The Empirical Model

5.1 Specification

We do not attempt to construct a time–series model of commodity prices that can be used, for example, for prediction. Instead, we are interested in explaining variations in low–order moments of price distributions over time and across commodities.

The general form of the equations that are estimated is

$$y_{kit} = \alpha_{ki} + \beta_k^T m_{it} + \gamma_k^T A_{it} + \delta_k^T x_{kit} + u_{kit}, \quad k = 1, 2, \quad i = 1, \ldots, 6, \quad t = 1, \ldots, 108, \tag{1}$$

where i is a commodity, t is a month, y_{kit} is an average price ($k = 1$) or price volatility ($k = 2$), m_{it} is a vector or scalar of market–structure measures (HHI or CR4), A_{it} is a vector or scalar of financial–market–activity variables (TURN or OPEN), x_{kit} is a vector of supply/demand variables that can include a trend, and u_{kit} is a zero–mean random variable. Finally, $\alpha_k = (\alpha_{k1}, \ldots, \alpha_{k6})^T$ is a vector of commodity fixed effects.

The inclusion of commodity fixed effects implies that we assess how prices are affected by variations in the explanatory variables relative to their commodity–specific means. To illustrate, when we examine how price levels vary with concentration, we assess how deviations in concentration from commodity–average concentration affect deviations in prices from commodity–average prices, where prices have been normalized and are thus comparable. Furthermore, the assessment is conditioned on deviations in cost factors from their average values.

In spite of the fact that our estimating equation is very simple, there are at least five econometric issues that must be dealt with: the possibility that some variables might be nonstationary, the issue of endogeneity of some of the explanatory variables, the question of whether the specification should be dynamic, the fact that some variables are measured at monthly intervals whereas others are measured yearly, and the choice of an error–covariance structure.

First consider the stationarity issue. Of the variables in equation (1), prices are most apt to be nonstationary. However, there is little agreement on this issue. In particular, IO researchers often assume that prices are stationary, whereas researchers from finance typically assume that they are not.[23] Furthermore, tests for the presence of unit roots in commodity prices yield conflicting results.[24] Since this is a much studied issue, we do not attempt further tests here. Instead, despite the mixed evidence, we assume that all of our variables are mean reverting. We do this for two reasons: we feel that the evidence in favor of nonstationarity is not compelling, and we worry that, if we filter our data, our results might be sensitive to the filter chosen.

Second, all of the financial variables in our model are apt to be jointly determined and therefore endogenous. In particular, we believe that trading activity and inventories are jointly determined with price levels and volatilities.[25] Furthermore, the endogeneity problem worsens as the period between observations, Δt, lengthens. We therefore use an instrumental–variables (IV) technique to correct for simultaneity.

Although the use of monthly (as opposed to daily or hourly) data exacerbates some problems (e.g., simultaneity), it mitigates others. Indeed, many models of futures–price determination focus on dynamic issues. Dynamics can appear in equation (1) in two ways: lagged variables can be included on the right–hand–side of the equation, and the error, u, can have a dynamic specification (e.g., serial correlation and/or heteroskedasticity across time).[26] The data that are used to estimate futures–price models, however, are typically daily, and the specification typically includes lags of

[23] There are, however, exceptions (e.g., Fama and French 1988, who assume mean reversion).

[24] Some studies conclude that prices are nonstationary, but others find evidence of mean reversion, e.g., Hamilton (1992), Bessembinder *et. al.* (1995), Deaton and Laroque (1996), Schwartz (1997), Pindyck (1999), and Slade (2001).

[25] The forward price is also jointly determined with the spot price. However, we do not focus on the relationship between spot and forward prices, and equation (1) is a partial reduced form that includes only the endogenous variables of interest.

[26] In our estimation, we correct for serial correlation of an unknown form.

less than two weeks. Furthermore, some researchers find that the temporal relationship between futures–price variability and financial variables such as volume is largely contemporaneous (e.g., Foster 1995). Given that our spot–price data are monthly, dynamics are apt to play a less important role. Furthermore, we face a practical problem in modeling dynamics – most of our data are measured at monthly frequencies, but some are measured yearly. Monthly lags of the latter variables of up to eleven periods could therefore be constant. For these reasons, we specify a static model. Unfortunately, failure to include lagged explanatory variables when appropriate could result in biased estimates. The use of instruments, however, overcomes this problem.

To illustrate, consider the possibility that lagged trading activity, A_{it-j}, $j > 0$, belongs in (1). If it is inappropriately excluded, it will be incorporated into u. Furthermore, if trading activity is itself autocorrelated, the current value, A_{it}, will be correlated with u. However, projections of A_{it} onto the instruments will be not be correlated with u.

Next, consider the frequency of the data. Unlike trading activity, market structure changes very slowly and can be considered a state variable. Even if we had monthly data on market structure, there would therefore be little month–to–month variation in that data. We model the situation as follows.

Suppose that there is a single market–structure index[27] and that the yearly value of that index, $\tilde{M}$, has two components, one that is specific to commodity i and one that is common to all commodities, $\tilde{M}_{iT} = M_{iT} + \mu_T$, where T is a particular year. The monthly value is then $m_{it} = \tilde{M}_{iT} + v_{it}$, where t is a month in year T, and v is measurement error. Under this specification, equation (1) becomes

$$y_{kit} = \alpha_{ki} + \beta_k M_{iT} + \gamma_k^T A_{it} + \delta_k^T x_{kit} + \eta_{kT} + w_{kit}, \tag{2}$$

where η_{kT} is a vector of yearly fixed effects, and $w_{kit} = u_{kit} + \beta_k v_{it}$. We assume that monthly measurement error is mean independent of the yearly market–structure index, $E[v_{it}|\tilde{M}] = 0$. However, since contemporaneous correlation between monthly observed activity and unobserved measurement error, A_{it} and v_{it}, is likely, the application of OLS to (2) could yield biased estimates. As with dynamic considerations, however, the use of instruments overcomes this problem.

Finally, we must choose a stochastic specification for w. The two equations, one for the level and one for the volatility of prices, can be written in matrix notation as

$$y = Z\theta + w, \tag{3}$$

[27] The same argument holds with a vector of market–structure indices.

where y (w) is the stacked vector of dependent variables (errors), Z is the matrix of explanatory variables, and θ is a stacked vector of parameters. Linkages across commodity markets imply that shocks to one market can be transmitted to related markets. We therefore expect contemporaneous correlation in w across commodities in each equation, and we specify a full cross–sectional covariance matrix $\Sigma^k = [\sigma^k_{ij}], i, j = 1, \ldots, 6, k = 1, 2$. The covariance matrix for w is then

$$\Omega = VAR(w) = \begin{pmatrix} \Sigma^1 \otimes I_{108} & \tilde{\sigma}_{12} I_{648} \\ \tilde{\sigma}_{12} I_{648} & \Sigma^2 \otimes I_{108} \end{pmatrix}$$

where $\otimes$ is the Kronecker product, and $\tilde{\sigma}_{12}$ is the covariance between the errors in the two equations.

5.2 Estimation

If B is the matrix of instrumental variables, the estimator of θ is

$$\hat{\theta} = (Z^T B(B^T \Omega B)^{-1} B^T Z)^{-1} Z^T B(B^T \Omega B)^{-1} B^T y. \tag{4}$$

.

We estimate θ in two steps as follows:

Step 1: Estimate equation (4) with Ω replaced by an identity matrix. This equation is used to estimate Ω, which gives $\hat{\Omega}$.

Step 2: Reestimate equation (4) with Ω replaced by $\hat{\Omega}$ from in step 1. This procedure yields an estimate, $\hat{\theta}$, that is consistent and, if the dynamic specification for w is correct, it is (asymptotically) optimal.

If the errors are serially correlated, $\hat{\theta}$ will still be consistent, but the estimated standard errors of $\hat{\theta}$ will not be. As autocorrelation is apt to be a problem, especially in the price equation, we used the Newey and West (1987) procedure to obtain a covariance–matrix estimator that is valid in the presence of serial correlation of an unknown form.[28]

5.3 Identification and Tests of Instrument Validity

There are three endogenous right–hand–side variables in equation (3): TURN, OPEN, and STOCK. To achieve identification, we created two sets of instruments. First,

[28] We use the Newey/West procedure to correct for serial correlation but not for heteroskedasticity, which we model as in subsection (5.1).

we interacted the market–structure variables, which differ by commodity but not by month, with the supply/demand variables, which differ by month but not by commodity.

Second, we exploited the inter–connectedness of commodity markets. In particular, silver was not traded on the LME during the period of interest and therefore does not appear in our data. However, due to spillovers across markets, trading activity in silver should be correlated with trading activity in the other metals. We therefore use silver turnover, open interest, and inventories on the Commodity Exchange of New York (COMEX) as instruments.[29] In so doing, we assume that the only link between silver–trading activity and, for example, copper price, is through copper–trading activity.

Formally, we assume that $E[S_t w_{it}] = 0$, where S_t is a measure of silver trading volume or stocks. However, since it is not immediately obvious why this assumption is valid, we discuss the circumstances under which this will and will not be the case. The error u in equation (1) can be decomposed into three parts, demand, cost, and trading shocks. First consider demand. The principal uses of silver (in photographic materials, jewelry, and tableware) are very different from the uses of the other metals. It therefore seems reasonable to assume that demand shocks are uncorrelated across commodities.[30] Next consider costs, which are more problematic. In particular, joint production (e.g., silver/copper) is common, and correlated cost shocks could destroy the validity of the instruments, especially of silver inventories, which is a proxy for supply/demand imbalance. Finally, consider trading shocks, which can be decomposed into three components: one that is commodity specific, one that is exchange specific, and one that is global. Only the third presents a potential problem for the validity of our instruments, and this problem is mitigated by the inclusion of time–period fixed effects.[31]

The exogeneity of some of our instruments can clearly be questioned. The issue, however, cannot be resolved theoretically and must ultimately be determined empirically. We therefore employ a formal test of exogeneity that is developed in Pinkse and Slade (2001). Consider the estimating equation (3) and suppose that r_{it} is the suspect instrument, Q_{it} is the set of non-suspect instruments, Z_{it} is the

[29] COMEX is now a division of the New York Mercantile Exchange (NYMEX). Data for these variables are published in American Metals Market.

[30] Aggregate demand shocks are removed through the use of time–period fixed effects.

[31] The fact that there might be exchange–specific (LME) shocks is the principal reason why we use silver variables rather than comparable variables for other commodities in the sample. In particular, the fact that the errors, u_i and u_j are correlated does not imply that, for example, the activity variables, A_j are correlated with u_i. This means that A_j could be a valid instrument for A_i, where i and j are both in the sample.

set of explanatory variables that includes at least one endogenous regressor, and w_{it} is the error for commodity i in period t. For r to be a valid instrument, w and r must be element–wise uncorrelated, i.e. $E[r_{it}w_{it}] = 0$. Let $P_Q = Q(Q^TQ)^{-1}Q^T$, $M = I - Z(Z^TP_QZ)^{-1}Z^TP_Q$, $\tilde{V} = r^TM\hat{\Omega}M^Tr$, where $\hat{\Omega}$ is our estimate of Ω, and $\hat{w}$ be the residuals from an IV estimation using Q (but not r) as instruments. Then, under mild regularity conditions on $\hat{\Omega}$,

$$\tilde{V}^{-1/2}r^T\hat{w} = \tilde{V}^{-1/2}r^TMw \tag{5}$$

has a limiting $N(0,1)$ distribution.

If one wants to test more than one instrument at a time, it is possible to use a matrix R instead of the vector r. Indeed, if $\tilde{V} = R^TM\hat{\Omega}M^TR$, the quantity

$$\hat{w}^TR\,\tilde{V}^{-1}R^T\hat{w} \tag{6}$$

has a limiting χ^2 distribution with degrees of freedom equal to the number of instruments tested.

5.4 Testing the Theoretical Models

The principal testable predictions of the theoretical models are summarized in Tables 1 and 2. The way in which our estimating equation can be used to test those predictions, however, deserves further discussion.

First consider the relationship between prices and market structure. Many IO models predict that marginal profits, π_i, not prices, p_i, will be related to market structure, M_i. In other words the prediction is that

$$\pi_{it} = p_{it} - mc_{it} = \alpha + \beta M_{it} + u_{it}, \tag{7}$$

where mc is marginal cost and M is a measure of market structure. If marginal cost is a function only of factor prices, v, $mc_{it} = f_i(v_t)$,[32] equation (7) can be written as

$$p_{it} = \alpha + \beta M_{it} + f_i(v_t) + u_{it}. \tag{8}$$

Rather than modeling profits, we include factor prices on the right–hand side of our estimating equation, as in (8). This specification has the advantage of allowing us to assess the effect that market structure has on prices, holding costs constant.

In order to test another prediction, a change should be made to equation (1). Indeed, with the Allaz (1992) and Allaz and Villa (1993) models, the predicted effect

[32] This will be true under constant returns.

of trading activity on the price level depends on the structure of the market. In particular, the effect disappears as the market approaches perfectly competitive. This implies that the interaction between market structure and trading activity, not the volume of activity *per se*, matters. To test this hypothesis, we created an interaction variable, HHIX = HHI × X, where X stands for turnover (X = T) or open interest (X = O) and added that variable to the price–level equations.[33]

Unfortunately, there are more models than testable predictions, which makes it difficult to distinguish among theories. However, we can exploit our instrumental–variables estimator to distinguish between two classes of models that yield the same predictions concerning the relationship between trading activity and price volatility. Indeed, with some models (e.g., the destabilizing–speculation models) there is a direct link between activity and volatility. With other models (e.g., the exogenous–information models), in contrast, there is no direct link. When the correlation between trading volume and price volatility is driven by an underlying latent variable and there is no direct link, OLS estimates of equation (2) will indicate that volume and volatility are positively correlated. This correlation will disappear, however, when instruments are used.[34] When there is a direct link, in contrast, the correlation should survive the use of instruments.

Figure 4 illustrates our point in the context of an informational model. In this figure, y_1 is price volatility, y_2 is trading activity, and z_i is an instrument that shifts y_i but not y_j, $j \neq i$. Finally, x is an informational variable that shifts both y_i and y_j. In the first half of the figure, (A), there is no direct connection between the two endogenous variables, whereas in the second half, (B), there is feedback between the two. The figure shows that shifts in one of the instruments (the z's) will cause both endogenous variables to move in panel B but not in panel A.

6 Empirical Results

The two equations in the system explain the level and volatility of spot prices. We present two sets of estimates of each system. The first set consists of OLS regressions, whereas the second is estimated by the IV method that is described in subsection 5.2. All specifications include cost variables. To save on space, however, the coefficients of those variables are not shown.

[33] TURN and OPEN do not appear directly in the price–level equations that are estimated because they are highly correlated with HHIT and HHIO. In particular, the estimated coefficients in equations that include both measures of activity are highly unstable.

[34] Our argument assumes that the instruments do not include the latent informational variables, which is apt to be the case in our application.

Some specifications of the equations include commodity fixed effects that allow the mean of each variable to differ by cross section. This implies that identification is achieved through variation in the time dimension. We also estimate specifications that do not include commodity fixed effects. Those equations are principally identified through variation in the cross section. This is true because, with many variables, cross–sectional variation dominates time–series variation.

6.1 The OLS Estimates

The OLS estimates appear in the top halves of Tables 4 and 5. The six specifications of each equation differ according to the measure of trading activity that is used and according to the inclusion of commodity and/or yearly fixed effects.

First consider the equations that explain spot–price levels. Table 4 provides strong evidence that a more concentrated industry is associated with higher prices, as the conventional wisdom predicts. Indeed, the market–structure variable is significant at 5% in 5 out of 6 specifications. Furthermore, prices appear to be higher when trading activity and inventories are low, and when industrial production is high, and many of those findings are also significant at conventional levels. The specifications that do not include yearly fixed effects include a trend. The estimated coefficients of that variable show that there was a significant downward trend in real prices during the decade, a regularity that can also be detected in Figure 1.

The equations that explain volatility are found in Table 5. That table shows that the relationship between volume and volatility is positive and highly significant, regardless of the measure of trading activity that is used. In addition, volatility is significantly higher when industrial production is high. Other patterns change, however, according to whether identification is achieved through variation in the cross section or in the time series. Indeed, product–market concentration and price volatility are negatively and significantly related in the cross section (specifications 1 and 4). However, the direction of this effect reverses and loses most of its significance when identification is achieved through time–series variation. Furthermore, there is a significant positive relationship between inventory levels and price volatility in the cross section, but much of its significance disappears when cross–sectional variation is removed.[35]

[35] Our finding can be contrasted with that of Brunetti and Gilbert (1996), who find a negative relationship between volatility and inventory levels in time–series data.

6.2 The IV Estimates

The bottom half of Table 4 contains IV estimates of the price–level equation. The table shows that virtually all of the empirical regularities that were found in the OLS estimates persist in the IV estimates. Furthermore some of the results are strengthened. In particular, the market–structure effect is more significant.

The situation is different, however, when we consider the volatility equations in Table 5. In particular, some regularities that appear in the OLS estimates fail to persist in the IV estimates. The most important pertains to the relationship between trading volume and price volatility. Indeed, when OLS is used, this relationship is positive and highly significant in all specifications. However, when instruments are used the relationship is insignificant in five out of six specifications.

We performed a number of tests of instrument validity. First, we assessed whether the additional instruments (those that are not included in the estimating equation) explain the endogenous right–hand–side variables and found that they have high explanatory power (R^2s over 0.5). Second, we assessed whether the instruments are correlated with the errors. When we used equation (5) to test the exogeneity of our instruments, our results were somewhat mixed. Specifically, the silver stocks variable failed the exogeneity test.[36] For this reason, we re–estimated the IV specifications without that instrument but found little change in our estimates.

We assessed robustness by considering alternative specifications of the interaction between market structure and trading activity. In particular, we created a second set of interaction variables by multiplying a dummy that equals one if the commodity market is moderately concentrated and zero otherwise times our measures of trading activity. When the new interaction variables were included in the price equations, their estimated coefficients were negative and highly significant. Furthermore, when TURN and OPEN were included in the price equations without interaction, their coefficients were also negative and generally significant.

We also experimented with an alternative measure of price, ln(PS), and with an alternative measure of market structure, CR4. Moreover, we used percentage changes in the demand and cost factors instead of levels in the volatility equations. The alternative specifications, however, did not cause us to alter the qualitative nature of our conclusions.

Finally, we experimented with versions of the econometric model in which the error covariances in equation (5.1), $\tilde{\sigma}_{12}$, were allowed to vary by commodity and with

[36] Note that this is what one would expect if the problem is due to correlated cost shocks (see subsection 5.3).

versions with full price–level/volatility covariance matrices. However, the results were not qualitatively different from those reported.

The models that we examine attempt to explain the behavior of spot prices. Nevertheless, some forward contracts result in delivery, which implies that forward prices are also 'real' or product prices. It is therefore of interest to see how product–market structure and forward–market trading affect forward–price distributions.[37] Tables 6 and 7 are comparable to 4 and 5 except that moments of forward–price distributions, PFR and LSIGPF, replace PSR and LSIGPS as dependent variables. Those tables show that the results for forward and spot prices are very similar to one another.[38]

6.3 Comparisons Between Theory and Evidence

We are now in a position to evaluate the comparative–static predictions that are listed in Tables 1 and 2. The most important empirical regularities are summarized in those tables under the heading of "In Our Data."

6.3.1 Product–Market Structure

The robust, significant, and positive relationship between product–market concentration and the price level that we find confirms the conventional wisdom that market structure matters.[39] As we noted earlier, there are a number of theoretical models that predict that there will be no such relationship. In particular, the Allaz and Villa (1993) model of frequent financial–market trading followed by Cournot behavior in the spot market yields that prediction. We, however, find no evidence that the existence of forward markets in which firms can trade continuously eliminates the market power of those firms.

Turning to the relationship between product–market concentration and price volatility, the IO models that we discussed predict that this relationship will be negative. We find that this prediction is confirmed when identification is achieved principally through cross–sectional variation. In other words, we find that commodities that are produced in more concentrated markets tend to have more stable prices. When identification is achieved through time–series variation, however, the relationship becomes positive but looses its significance.

[37] Performing the analysis using forward prices was suggested by a referee.

[38] The one exception is that the volume/volatility relationship is stronger for the forward price, a result that is consistent with the finance literature (see, e.g., Karpoff 1987).

[39] Recall that we assess the price level conditional on cost and demand factors.

6.3.2 Forward–Market Trading

We have argued that the interaction between trading activity and market structure could be an important determinant of the spot–price level. Moreover, we find that, not only does increased trading lower price, but also that that relationship is stronger when commodity markets are more concentrated. This empirical regularity is consistent with the Allaz (1992) and Allaz and Villa (1993) models, in which commitment to sell forward lowers the spot–market price by removing some units of output from the spot–market game.

In theory, a negative relationship between trading activity and the price level could also result from either an increase in supply or a reduction in transactions costs. It seems unlikely, however, that month–to–month changes in liquidity cause short–run changes in production plans. In particular, production schedules are apt to be based on a longer time horizon. Furthermore, even though the reduced transactions costs that are associated with thicker markets could lead to lower prices, this relationship should be independent of the structure of the market.

With respect to forward trading and volatility, we reiterate that, whereas the predictions of the destabilizing–speculation models are mixed, exogenous arrival of information should result in a positive relationship between the two variables. The correlation that is found in our data is positive and, with the OLS estimations, it is significant.

We are able to say more, however. In particular, as outlined in section 5.4, if there is a direct link between trading volume and spot–price volatility, the positive relationship should survive the use of instruments. If the correlation is due to a common–causal factor or latent variable, in contrast, the significance of the relationship should disappear when instruments are used. We find that the significance of the relationship does indeed virtually disappear when we use instruments. This suggests that the link between the two is not direct and that both variables are influenced by a common factor such as the arrival of new information.[40] Our findings are thus consistent with a simple model, but not with the more sophisticated theories that we discuss.

[40] One might wonder whether the lack of significance of the coefficients of the measures of volume is due to the use of instruments or to the correction for heteroskedastic and autocorrelated errors. Since the first–step estimates are very similar to the second, it is clear that the lack of significance is due to the use of instruments.

7 Conclusions

We have attempted to disentangle the effects that product and forward markets have on spot–price levels and volatilities. One motive for undertaking that exercise is to test the many theories that link the two markets. There is an additional reason, however. Indeed, government agencies have some control over product–market structure and take an active role in policing concentration in the physical market. However, although they regulate the terms of trade in forward markets, governments are usually unwilling to control the volume of trade and tend to intervene in financial markets only in extreme situations.

To summarize, we find that traditional market–structure models, in which price levels are positively related to product–market concentration, perform well. In particular, we find no evidence of the complete unraveling that is predicted to lead to competitive pricing in commodity markets with continuous forward trading (e.g., Allaz and Villa 1993). This means that merger policy is not irrelevant in these industries.

Furthermore, the market–structure effects that we uncover are economically large. Indeed, we estimate a typical elasticity of price with respect to the HHI to be 0.2.[41] This means that doubling the HHI is predicted to result in a 20% price increase. Given the size of the markets, that change would lead to a substantial increase in company revenues.

Turning to financial–market activity, increased liquidity appears to be associated with lower prices. We argue that this relationship could be strategic, as in the Allaz (1992) model. If our finding is robust, it could be important. Indeed, economists have advocated the creation of opportunities for forward and long–term contracting in other commodity markets such as electricity. In so doing, they have relied partially on the insight that contractual lockin causes prices to fall (see, e.g., Borenstein 2002, and for other views, Powell 1993 and Green 1999).

Finally, as with most empirical studies of futures prices, we find a positive time–series relationship between trading volume and the volatility of spot prices. Moreover, since we deal with multiple related markets, we are able to assess that relationship in the cross section, and we find that it is also positive. Our findings are consistent with the predictions of many destabilizing–speculation and informational models. We can, however, go further. Indeed, we are able to exploit our instrumental–variables technique to distinguish between broad classes of theories that predict a positive relationship. When we do this, we find evidence that the link is not direct and that there is no feedback between volume and volatility. Rather the correlation appears to

[41] This is a conservative estimate, and with many specifications, the elasticity is larger.

be due to an unobserved variable such as the arrival of new information that affects volume and volatility simultaneously.

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Table 1: Predicted Effects of Product–Market Concentration

Type of Model		Effect on Price Level
IO	Cournot (1838)	+
	Bertrand (1883)	0
	Allaz (1992)	+
	Allaz and Villa (1993)	0
	Thille and Slade (2000)	+
In Our Data		+

		Effect On Volatility
IO	Newbery (1984a)	-
	Newbery (1990)	-
Real Options		-
In Our Data		- in Cross Section

Table 2: Predicted Effects of Financial–Market Liquidity

Type of Model		Effect on Price Level
Informal Stories		-
IO	Allaz (1992)	-
	Allaz and Villa (1992)	-
In Our Data		-

		Effect on Volatility
Destabilizing Speculation		
Risk Reduction	Turnovsky (1979)	-
	Turnovsky and Campbell (1985)	-
	Kawai (1983)	+
	Newbery (1987)	+
Information Improvement	Cox (1976)	-
	Danthine (1978)	-
	Stein (1987)	+
Exogenous Information Arrival		+
In Our Data		+ with OLS
		0 with IV

Table 3: Summary Statistics

Variable	Units	Mean	S.D.	Minimum	Maximum	
Spot Price (PSR)	Unit free	843	172	470	1529	
Spot–Price Volatility (SIGPS)		1.38	0.71	0.35	7.56	
Forward Price (PFR)	Unit free	852	164	488	1505	
Forward–Price Volatility (SIGPF)		1.23	0.55	0.27	4.97	
Turnover (TURN)	%	9.29	5.64	1.04	37.3	
Open Interest (OPEN)	%	3.36	3.76	0.22	16.7	
HHI	Index	659	463	99	1785	
CR4	%	37.5	15.2	16.0	69.0	
Inventories/Production (STOCK)	%	9.73	11.6	0.07	63.2	
Industrial Production (IP)	Index	97.6	2.46	93.3	108	
Energy Price (ENP)	Index	99.9	2.01	94.8	105	
Hourly Earnings (WAGE)	Index	107	4.01	97.9	115	
Mining Machinery and Equipment (MME)	Index	101	0.85	98.8	103	
Interest Rate (INT)	%	5.92	2.14	3.70	10.0	
Statistics by Commodity						
			Mean			
	PSR	SIGPS	TURN	OPEN	HHI	STOCK
Aluminum	870	1.15	8.15	1.28	486	6.96
Copper	891	1.48	13.66	1.69	361	3.07
Lead	780	1.70	3.42	0.60	127	1.30
Nickel	910	1.61	9.82	6.13	1139	26.73
Tin	797	1.04	12.57	9.18	1392	10.75
Zinc	808	1.33	8.15	1.25	449	9.56

Table 4: Spot–Price Level Equations[a]

OLS

#	HHI	HHIT	HHIO	STOCK	TREND	IP	Fixed Effects[b]	R^2
1	0·033	−0·0014		0·76	−2·91**	24·92**		0·45
	(0·024)	(0·0013)		(0·59)	(1·06)	(3·47)		
2	0·119*	−0·0011		−1·79*	−4·00**	25·70**	C	0·54
	(0·060)	(0·0015)		(0·76)	(0·99)	(3·21)		
3	0·181**	−0·0029*		−2·80**		26·26**	C&Y	0·63
	(0·054)	(0·0013)		(0·72)		(5·93)		
4	0·117**		−0·0090**	0·42	−3·55**	25·31**		0·47
	(0·025)		(0·0019)	(0·57)	(1·05)	(3·39)		
5	0·167*		−0·0025	−1·46	−4·06**	25·89**	C	0·54
	(0·070)		(0·0026)	(0·83)	(0·99)	(3·18)		
6	0·275**		−0·0083**	−1·99*		25·68**	C&Y	0·64
	(0·064)		(0·0024)	(0·77)		(5·90)		

IV

#	HHI	HHIT	HHIO	STOCK	TREND	IP	Fixed Effects[a]	R^2
1	0·057	−0·0047**		1·91*	−2·56	19·08**		0·44
	(0·035)	(0·0019)		(0·94)	(1·63)	(5·63)		
2	0·373**	−0·0071**		0·56	−3·23*	22·06**	C	0·53
	(0·078)	(0·0021)		(1·43)	(1·63)	(5·45)		
3	0·394**	−0·0099**		−1·34		24·24**	C&Y	0·62
	(0·079)	(0·0021)		(1·36)		(7·73)		
4	0·090**		−0·0094**	1·78*	−3·18	22·46**		0·46
	(0·035)		(0·0025)	(0·85)	(1·66)	(5·76)		
5	0·511**		−0·0154**	3·28*	−2·94	21·99**	C	0·53
	(0·098)		(0·0038)	(1·59)	(1·64)	(5·50)		
6	0·589**		−0·0208**	2·71		22·56**	C&Y	0·62
	(0·098)		(0·0038)	(1·57)		(7·88)		

[a] Price relative to the price of the commodity in January 1990 times 1000.
[b] C means commodity fixed effects and Y means year fixed effects.
Standard errors in parentheses. IV standard errors corrected for heteroskedasticity and for serial correlation of an unknown form.
* denotes significance at 5%, ** denotes significance at 1%
Cost variables included but not shown.

Table 5: Spot–Price Volatility Equations[a]

OLS

#	HHI	TURN	OPEN	STOCK	TREND	IP	Fixed Effects[b]	R^2
1	−0·034**	2·00**		0·93**	−0·38	8·56**		0·22
	(0·004)	(0·40)		(0·18)	(0·32)	(1·06)		
2	0·025	4·84**		0·32	−0·60*	8·16**	C	0·41
	(0·014)	(0·52)		(0·22)	(0·29)	(0·94)		
3	0·019	4·60**		0·18		4·99**	C&Y	0·45
	(0·013)	(0·52)		(0·22)		(1·87)		
4	−0·056**		4·62**	0·76**	−0·28	8·89**		0·22
	(0·008)		(1·03)	(0·18)	(0·33)	(1·06)		
5	0·022		4·95**	0·04	−0·66*	9·45**	C	0·34
	(0·018)		(1·24)	(0·27)	(0·30)	(0·98)		
6	0·015		4·62**	−0·22		5·85**	C&Y	0·40
	(0·017)		(1·21)	(0·27)		(1·96)		

IV

#	HHI	TURN	OPEN	STOCK	TREND	IP	Fixed Effects[b]	R^2
1	−0·023**	−0·360		0·90**	−0·51	9·19**		0·20
	(0·006)	(0·53)		(0·23)	(0·47)	(1·56)		
2	0·048**	1·71		0·81*	−0·57	9·02**	C	0·39
	(0·017)	(1·12)		(0·37)	(0·44)	(1·46)		
3	0·050**	0·990		0·59		5·57*	C&Y	0·42
	(0·016)	(1·13)		(0·37)		(2·61)		
4	−0·053**		4·17**	0·84**	−0·30	8·86**		0·21
	(0·011)		(1·40)	(0·24)	(0·47)	(1·53)		
5	0·054*		0·82	0·77	−0·63	9·62**	C	0·32
	(0·023)		(1·79)	(0·47)	(0·46)	(1·48)		
6	0·049*		0·84	0·46		5·81*	C&Y	0·39
	(0·021)		(1·72)	(0·48)		(2·66)		

[a] Log of standard deviation of % changes in real spot prices times 100.
[b] C means commodity fixed effects, Y means year fixed effects, and blank means no fixed effects. Standard errors in parentheses. IV standard errors corrected for heteroskedasticity and for serial correlation of an unknown form.
* denotes significance at 5%, ** denotes significance at 1%
Cost variables included but not shown.

Table 6: Forward–Price Level Equations[a]

OLS

#	HHI	HHIT	HHIO	STOCK	TREND	IP	Fixed Effects[b]	R^2
1	0·030	−0·0026*		1·43*	−2·27*	22·49**		0·44
	(0·023)	(0·0013)		(0·57)	(1·02)	(3·34)		
2	0·101	−0·0006		−1·69*	−3·55**	23·20**	C	0·53
	(0·057)	(0·0014)		(0·73)	(0·95)	(3·07)		
3	0·165**	−0·0035**		−2·81**		24·87**	C&Y	0·64
	(0·051)	(0·0013)		(0·68)		(5·57)		
4	0·105**		−0·0096**	1·16*	−2·87**	22·61**		0·46
	(0·024)		(0·0018)	(0·55)	(1·01)	(3·26)		
5	0·150*		−0·0030	−1·34	−3·61**	23·30**	C	0·53
	(0·067)		(0·0025)	(0·79)	(0·95)	(3·05)		
6	0·258**		−0·0090**	−1·96**		24·22**	C&Y	0·65
	(0·060)		(0·0023)	(0·73)		(5·53)		

IV

#	HHI	HHIT	HHIO	STOCK	TREND	IP	Fixed Effects[a]	R^2
1	0·035	−0·0044*		2·83**	−1·71	16·88**		0·43
	(0·034)	(0·0018)		(0·95)	(1·61)	(5·57)		
2	0·354**	−0·0075**		0·40	−2·83	19·76**	C	0·53
	(0·076)	(0·0020)		(1·41)	(1·61)	(5·38)		
3	0·359**	−0·0097**		−1·58		23·30**	C&Y	0·64
	(0·077)	(0·0020)		(1·30)		(7·49)		
4	0·071*		−0·0091**	2·67**	−2·33	20·08**		0·45
	(0·034)		(0·0024)	(0·87)	(1·64)	(5·67)		
5	0·478**		−0·0150**	2·96	−2·60	19·76**	C	0·52
	(0·094)		(0·0035)	(1·53)	(1·62)	(5·44)		
6	0·547**		−0·0202**	2·26		21·53**	C&Y	0·64
	(0·094)		(0·0036)	(1·48)		(7·64)		

[a] Price relative to the price of the commodity in January 1990 times 1000.
[b] C means commodity fixed effects and Y means year fixed effects.
Standard errors in parentheses. IV standard errors corrected for heteroskedasticity and for serial correlation of an unknown form.
* denotes significance at 5%, ** denotes significance at 1%
Cost variables included but not shown.

Table 7: Forward–Price Volatility Equations[a]

OLS

#	HHI	TURN	OPEN	STOCK	TREND	IP	Fixed Effects[b]	R^2
1	−0·027**	1·30**		1·07**	−0·19	7·29**		0·17
	(0·004)	(0·39)		(0·17)	(0·31)	(1·02)		
2	0·029*	4·30**		0·44*	−0·41	6·83**	C	0·38
	(0·013)	(0·50)		(0·21)	(0·28)	(0·90)		
3	0·021	4·01**		0·21		5·37**	C&Y	0·43
	(0·013)	(0·50)		(0·22)		(1·79)		
4	−0·050**		4·24**	0·94**	−0·65	7·41**		0·18
	(0·008)		(0·98)	(0·17)	(0·31)	(1·01)		
5	0·023		4·78**	0·15	−0·46	7·95**	C	0·33
	(0·017)		(1·17)	(0·25)	(0·29)	(0·92)		
6	0·013		4·59**	−0·19		6·15**	C&Y	0·38
	(0·016)		(1·15)	(0·25)		(1·85)		

IV

#	HHI	TURN	OPEN	STOCK	TREND	IP	Fixed Effects[b]	R^2
1	−0·015*	−1·06*		0·89**	−0·34	7·69**		0·15
	(0·006)	(0·53)		(0·23)	(0·46)	(1·50)		
2	0·038*	2·70*		0·46	−0·48	7·16**	C	0·38
	(0·018)	(1·11)		(0·35)	(0·42)	(1·38)		
3	0·038*	1·92		0·19		5·71*	C&Y	0·41
	(0·016)	(1·13)		(0·36)		(2·56)		
4	−0·048**		3·99**	0·86**	−0·11	7·21**		0·17
	(0·011)		(1·33)	(0·23)	(0·45)	(1·45)		
5	0·046*		1·47	0·35	−0·57	7·94**	C	0·31
	(0·023)		(1·76)	(0·46)	(0·44)	(1·41)		
6	0·034		2·04	−0·15		6·16*	C&Y	0·38
	(0·021)		(1·70)	(0·47)		(2·63)		

[a] Log of standard deviation of % changes in real forward prices times 100.
[b] C means commodity fixed effects, Y means year fixed effects, and blank means no fixed effects.
Standard errors in parentheses. IV standard errors corrected for heteroskedasticity and for serial correlation of an unknown form.
* denotes significance at 5%, ** denotes significance at 1%
Cost variables included but not shown.

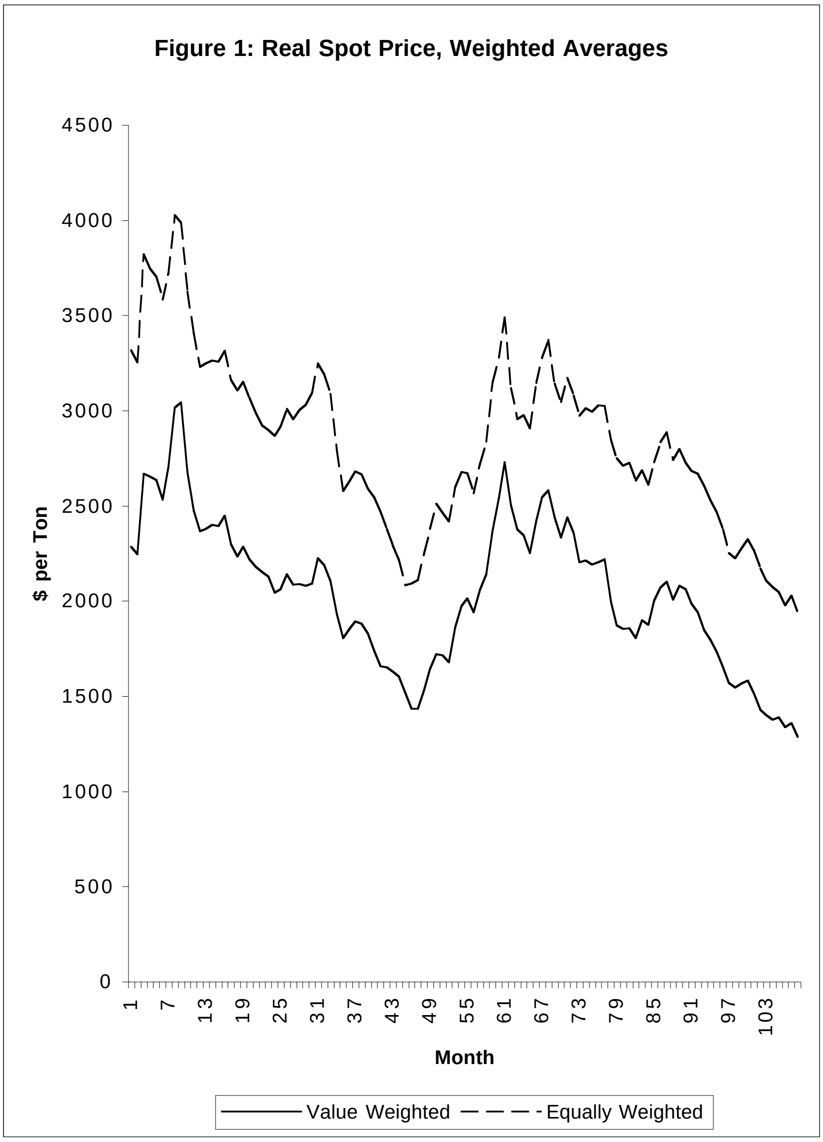
Figure 1: Real Spot Price, Weighted Averages
$ per Ton
4500
4000
3500
3000
2500
2000
1500
1000
500
0
1
7
13
19
25
31
37
43
49
55
61
67
73
79
85
91
97
103
Month
Value Weighted
Equally Weighted

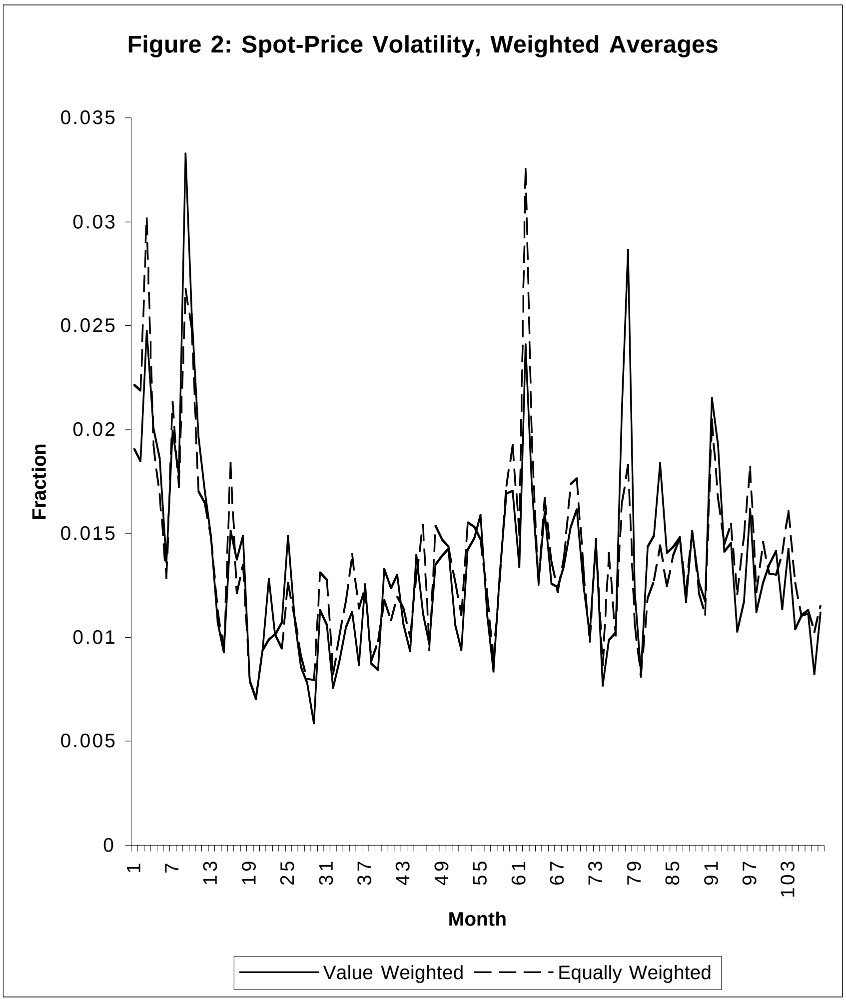
Figure 2: Spot-Price Volatility, Weighted Averages
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
Fraction
1 7 13 19 25 31 37 43 49 55 61 67 73 79 85 91 97 103
Month
Value Weighted
Equally Weighted

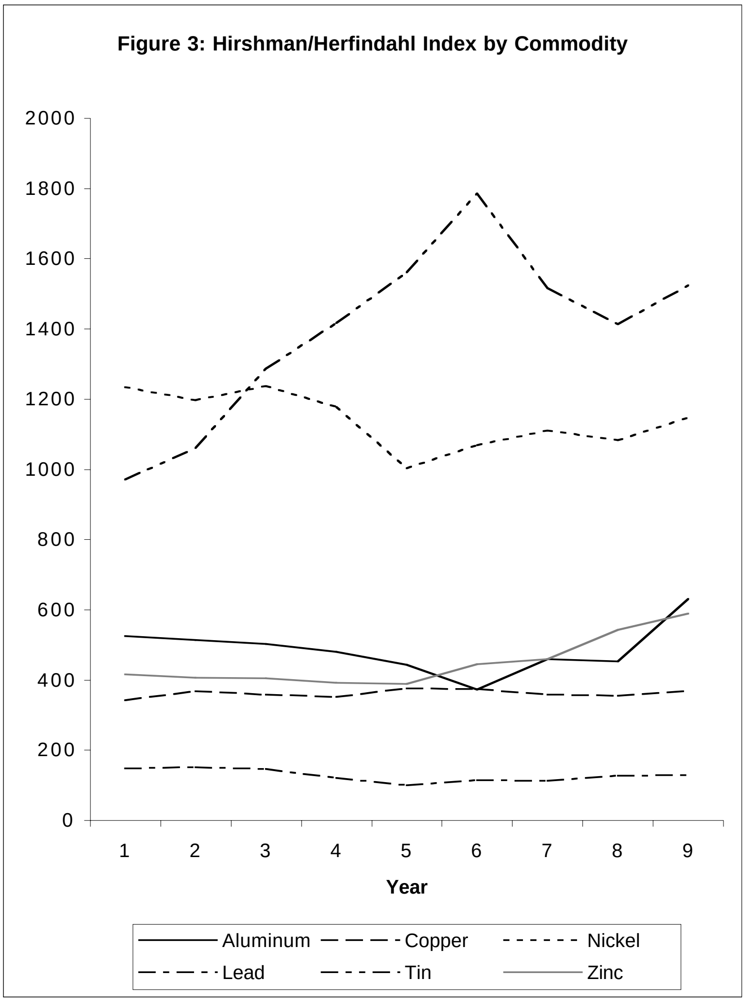
Figure 3: Hirshman/Herfindahl Index by Commodity
2000
1800
1600
1400
1200
1000
800
600
400
200
0
1
2
3
4
5
6
7
8
9
Year
Aluminum
Copper
Nickel
Lead
Tin
Zinc

Figure 4

Distinguishing Between a Direct Link and a Common Causal Factor