A cross-county comparison of stock reactions to price changes in commodities

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Abstract

We examine whether there is a difference between equity markets' in the speed at which stock prices reflect new commodity prices. Our study is based on daily commodity price data, and stock data from the Scandinavian main exchanges and the London Stock Exchange. To explore the potential differences between stock markets, we estimate a simple market model with commodity lag terms and test for differences in reactions to commodity price changes across markets. We find no strong or consistent differences between the markets, and fail to generalize our findings. We conclude that the different stock markets behave in very similar ways on a daily level, but speculate that further studies with higher-frequency data could come to a different conclusion.

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1 INTRODUCTION

It is well-known and obvious that the price of a commodity is reflected in the stock prices of firms that deal with the commodity.[1] For some industries and companies, this effect is minor. For some, however, the effect can be considered a primary source of volatility in their respective share prices. This would seem to be especially true for the mining industry dealing in precious metals, as noted by Tufano (1998). However, it is less clear how rapidly stock prices incorporate new information and whether the speed differs between markets. If one could find a systematic difference in speed of incorporation between markets, it might be possible to earn abnormal profits by implementing commodity information faster in the slower market.

The rather special nature of commodities and commodity trading should be noted; commodities are notoriously volatile. Forecasting long-run trends is generally challenging, if not impossible, without the aid of insider information or clear general market outlooks.[2] With this in mind, it would also appear rational for markets to implement commodity price information in security pricing.

No journal or other scientific publication has tackled the relationship between commodities and stock prices across different equity markets. As such, influential literature that is relevant to the subject is scarce, and limited to no more than a handful of studies that are varyingly related to the subject. By combining the two separate kinds of studies, the commodity-stock relationship and a cross-market comparison, we feel that we contribute to the field of finance. The aim of this thesis is to investigate the relationship between market size and the reaction to news about commodity prices. We estimate the market reactions to commodity price changes for four different commodities: gold, silver, aluminium and copper. We test for the differences in mean values for the commodity betas, i.e. the effects of commodity price changes, across markets. We then conclude that the observed differences in values, although statistically significant, are too small to draw any general conclusions regarding differences in market behaviour or efficiency. The more generalised conclusion is that the efficient market hypothesis holds for the relevant markets.

[1] See for example Strong (1991)
[2] See for example Bowman et al (2004)

We form three hypotheses that guide our research:

Hypothesis 1

The different markets behave in the same way, i.e. reactions to commodity price changes are of similar or identical size and strength, exhibiting a similar or identical total reaction to commodity price changes during a three-day observation period.

The null hypothesis is rejected if there is a significant difference between markets in the total reaction to commodity price changes during the observation period [-2, 0].

Hypothesis 2

The different markets react to changes in commodity prices at similar or identical rates, exhibiting similar or identical values for each observation day.

The null hypothesis is rejected if there is a significant difference in the individual and combined effect of the lagged variables across markets.

Hypothesis 3

It is not possible to profit from an arbitrage opportunity created by differences in market efficiency, as the different markets implement information at sufficiently similar rates

The null hypothesis is rejected if significant differences in information diffusion across markets create an arbitrage opportunity where qualitatively similar securities are traded at considerably different prices on different markets.

To test these hypotheses, we begin by identifying companies that are particularly exposed to the prices of commodities on the London Stock Exchange and the three Scandinavian main exchanges. We then estimate a simple market model with the help of multiple regressions to acquire an understanding of how important the changes in commodity prices occurring today, yesterday, and the day before yesterday are for today's stock price in these companies. Then, we execute a series of tests for the difference in market reactions to commodity price changes to establish whether the markets' behaviour differ from each other in a statistically significant manner. By extension, this also means testing the efficient market hypothesis, according to which the new price information should be incorporated into stock prices at the same speed, or at the very least, as soon as information is available. In today's world, there is certain equivalence between the two statements. Using the above method we obtain statistically significant results on the differences between markets, but conclude that the estimated differences between markets are not of sufficient magnitude, nor of a sufficiently consistent and general nature, to imply a distinct and impactful difference between the two markets. Consequently, we fail to reject all but one of the null hypotheses, and conclude that the efficient market hypothesis hold for the examined markets.

2 PREVIOUS LITERATURE

To the best of our knowledge, there is no influential paper that does cross country comparisons of commodity and stock prices in the same or similar manner as we do. A large amount of the available literature focuses on the behaviour of commodity prices, particularly the speculated and often cited (excessive) co-movement of commodities. Another field with considerable amounts of research, and associated literature, is comparisons between international equity markets. Much of the research has a general focus on market efficiency, correlation and co-movement of markets and the interaction of markets in terms of transmission of information and volatility. An article by Tufano (1998) is closely related to the area of our study; the article examines the relationship between the price of gold and gold mining companies. By combining insights from all of these separate types of studies we get the theoretical framework required to tackle the problem at hand. We'll cover each category of these papers below.

2.1 The behaviour of commodity prices

Much of the financial literature on commodity prices is focused on oil. Oil, however, should be considered a special case compared to other commodities because of its particularly large effects on stock prices and macroeconomic variables, which could lead to unexpected and unexplainable results. Kilian and Park (2009) demonstrate this by showing that shocks in the price of crude oil can be used to explain as much as 22% of the variation in the US stock returns. They also mention that there are enormous endogeneity problems inherent in the relationship between oil prices and stock prices, since they affect each other in complicated ways. Therefore, despite oil's position as arguably the most important commodity in today's economy and its particularly interesting and observable effects on the global economy, we do not include oil, or other energy sources, in our study. One of the more studied areas is the co-movement of commodity prices.[3] Pindyck and Rotemberg (1988) started some controversy by claiming that the observed co-movements in commodities are "excessive", meaning they aren't fully explainable by any underlying shared macro- or microeconomic variables. This "puzzling phenomenon", as Pindyck and Rotemberg

[3] See for example Leybourne et al (1994), Palaskas and Varangis (1991) or Chatrath et al (2006)

call it, the tendency of commodity prices to move together, has attracted a considerable amount of attention. It is likely that this is at least partly because of its indirect assault on the efficient market hypothesis. A collection of studies has since discussed the phenomenon, with a number of studies apparently rebutting Pindyck's and Rotemberg's findings. Deb et al (1996) defend the notion of excess by co-movement, while Cashin et al (1999), claim to debunk the claimed "excessive" portion of the co-movement, and Ai et al (2006), present strong evidence evidence against the excess co-movement hypothesis. Whether or not this co-movement of commodity prices is excessive, however, is not of high importance to our study. The co-movement phenomenon itself is of some importance, as a similar behavioural pattern could be used to generalise results obtained from studying only a limited amount of commodities to some extent. There is also an inherent drawback to this behaviour: The co-movement of commodity prices could mean that studying four commodities fails in providing us four times the explanatory power of a single commodity.

2.2 The behaviour of stock markets

Many papers examine many different relationships between different stock exchanges. As previously mentioned, none of these studies actually conduct cross-country comparisons of the relationship with commodity prices, but there are still valuable lessons to be learned. Hamao et al (1990) and Karolyi and Stulz (1996) both make clear that there will be considerable biases when looking at daily data if the opening hours of the compared exchanges aren't synchronized. Using weekly rather than daily data would largely eliminate these biases, but then we would miss the price adjusting activity that interests us. In order to avoid the problem of non-synchronization we opt to use London Stock Exchange as the "large exchange" rather than, for example, the larger New York Stock Exchange. Masulis and Shivakumar (2002) do an interesting comparison on the speeds of two different stock markets. They found a statistically significant difference in speeds, but found much of the differences happen at the scale of 15 or 60 minute intervals. Ball (1978) also finds that a lot of the market reaction happens within minutes of the news shock. However, both these papers are from before the age of high frequency trading, which according to among others Brogaard et al (2012) has increased price efficiency. This tells us that we should perhaps be looking at data more frequent than daily if we want to capture all the activity.

2.3 Lessons from Peter Tufano's examination of the gold mining industry

Peter Tufano (1998) provides arguably the best description of a stock-commodity relationship in his influential paper, "The Determinants of Stock Price Exposure: Financial Engineering and the Gold Mining Industry". It is from him we borrow one of our most important formulas, which describes the relationship between daily changes in commodity prices and daily changes in stock prices. He found that the stock price of the average gold mining company moves two percent for every one-percent change in the price of gold. This gives us an indication of the magnitudes we can expect to find in our sample. He also notes that stock price exposure to gold prices varies significantly over time and between firms, which tells us that we must control for firm fixed effects, cluster by an appropriate time variable and perhaps avoid some time periods where exposure is unusually low. Furthermore Tufano provides a long list of variables that are important for commodity exposure. These include size, cost structure, choice of leverage, risk management policy and more. It is easy to imagine that one or several of these could differ systematically across the examined regions, which could provide the basis for different speeds of incorporation for stocks.

3 DATA

We use two different sources of data: one for commodity prices and one for stock prices. Our primary sources of data are the Thomson Reuters Datastream software, used for downloading the daily commodity prices data, and COMPUSTAT, which is used for the daily stock price data, both for the London Stock Exchange and the Scandinavian stock exchanges. They both have the common characteristic of high scrutiny and trustworthiness. All data cover every available trading day from the years 2002 through 2012.

3.1 Commodity data

We download the prices of the commodities via Thomson Reuters Datastream. We choose the most commonly quoted prices for the following commodities: gold, copper, silver and aluminium, from the London Buillion Market and the London Metal Exchange.[4] It should be noted that both the London Metal Exchange and the London Bullion market are highly established markets for the trading of certain metals, and can in some cases even be considered the de facto standard markets.

3.2 Stock data

The commodity data is merged with stock data from COMPUSTAT Global; we use the database Security Daily[5]. The resulting panel data consists of daily observations for all of the securities listed on the London Stock Exchange, the Scandinavian stock exchanges and the four commodities. The two datasets are kept separate to avoid excessively large data sets, leaving the London Stock Exchange data with 6 403 933 observations and 4064 unique securities and the Scandinavian stock exchanges with 2 293 852 observations and 1393 unique securities.

We use the London Stock Exchange as our ”large stock exchange”, while the Swedish, Norwegian and Danish main exchanges together form our ”small stock exchanges”. The Swedish, Norwegian and Danish exchanges are grouped together and essentially treated as a single market

[4]The exact names of these indices can be found in the appendix.
[5]See the appendix for a complete list of variables downloaded

and are referred to by the common name "Scandinavian".[6]

Since Compustat offers data by country rather than by exchange, when downloading data we inadvertently get some stocks that are listed on other exchanges than the main ones for each country. For example, our Scandinavian data even inexplicably includes a few firms from the Australian Stock Exchange. All firms not listed a main exchange are eliminated from the dataset. We also eliminate stocks that are not listed at least from the first day in 2008 and until the end of day of 2012. This is done in order to avoid biases caused by not having enough data for a particular company, delistings, bankruptcies, buy-outs or the volatile period following an IPO being a disproportionately large part of the data. We expect the effects of these events on stock prices to be much larger than any commodity price effect, and we don't want them distorting our results.

We actively choose to avoid the year of 2013, because many mining companies suffered great financial troubles from late 2012 and early 2013 to the end of 2013. When the market learns that a company might go bankrupt, the stock price will sink regardless of how the underlying commodity performs; this effect is particularly clear for the Scandinavian mining companies. The continuously sinking price of such security diminishes the importance of gold price in explaining the stock price.

[6]Note that the daily value weighted average return is naturally still calculated separately for each country

4 METHODOLOGY

To conduct the study on the differences between markets, we begin by estimating the commodity betas for both markets, utilising multiple regressions on a simple market model. The aim of these estimations is to acquire a general understanding of how changes in commodity prices affect the prices of securities. After obtaining the test results, we proceed to the second part of our study, executing a series of test for the difference in market reactions to commodity price changes. This is done by testing for the difference in mean values for the betas across markets, achieved by interacting the variables through the use of market dummy variables and re-estimating the market model to test the cross-model hypotheses.

4.1 Generating the basic variables

We begin by calculating the daily stock returns; as the data has a relatively high frequency, we use log returns both for the daily stock returns and the daily commodity returns. For the commodity returns, we also include two lag terms and one lead term. Adding one or more lag term has little effect on the measured betas in the sample, as also noted by Tufano. Since the purpose of the lead term is to control for whether stock markets lead the commodity markets, adding more than one lead term should be considered redundant, as such an effect should already be recorded and observed in a single lead term. The value-weighted returns for each of the four included markets are calculated as the daily returns for each individual security, weighted on total market capitalization, establishing the value of the daily value-weighted return as the weighted mean of all returns on particular trading day.

4.2 Measuring firms' exposures to commodities

We calculate exposures to changes in commodity prices by estimating the following market model:

$$R_{ct} = \alpha_c + \beta_c R_{ct} + \beta_{cm} R_{mt} + \beta_{cl} R_{ml} + \varepsilon_t$$

Where

R_{ct} is the logarithm of the daily return on stock c from t-1 to t

$R_{mt}$is the logarithm of the daily value-weighted market return from day t-1 to t for the country of listing.

$R_{ct}$is the logarithm of the daily return of the commodity price from day t-1 to t.

α_c is the constant term for the regression.

ε_t is the error term for the regression.

R_{ml} is the logarithm of yesterday's commodity return.

This regression is the same method used by Tufano (1996) when examining the gold mining industry.

We save the coefficients of the betas, and the associated standard deviations, which allows us to calculate each coefficient's t-value by dividing the coefficient by the standard deviation.

4.3 Defining "commodity exposed" companies

We use two different methods to define which companies are considered "exposed" to their underlying commodity. In the case of gold and silver we decide that all companies with a SIC (Standard Industry Classification) code of 1040, defined as "gold and silver ore", are considered exposed to the price of gold and silver price. As noted previously, there are some minor problems with the Scandinavian data in particular, with some firms facing severe financial troubles. From this group we exclude two companies completely[7] because their data behaves erratically.

In the cases of aluminium and copper there is no single SIC-code that is easily coupled to the prices of commodities. We therefore decide that firms that under a two-day observation period exhibit a combined coefficient value, i.e. reaction, that is greater than or equal to 0.3625, are

[7] Tricor PLC and Nickel Mountain Group

to be considered "aluminium-exposed".[8] We define the "copper-exposed" firms using the same reasoning and method as for aluminium, but with a cut-off value of 0.3408. By using a measure that combines the effects yesterday's commodity prices and today's commodity price, we are neutral in our selection regarding when the commodity affects today's stock price.

Please note that we won't introduce selection bias into our method as long as we are consistent across the countries for each individual commodity, so we aren't restricted to using the same methods to identify companies that are exposed to different commodities. Regardless of this, the underlying two groups of commodities, gold and silver, and aluminium and copper, should be noted when interpreting the results.

It is also worth noting that these groups of commodity-exposed securities differ significantly from the general market, exhibiting substantially different reactions to commodity price changes, while the market returns are very close to zero.[9]

4.4 Generating commodity price shock dummies

Since we are interested in finding out if the differences between markets are more pronounced when commodity price changes are stronger, we generate a dummy that is equal to 1 for the top and bottom 25% of daily price changes. This means that we avoid the middle 50% of data, which consists of price changes that are very close to zero. The exact cut-offs in terms of the logarithm of price change are:

- For gold, when the logarithm of the daily price change is greater than or equal to 0.72% or less than or equal to -0.53%.
- For silver, the equivalent numbers are 1.31% and -1.08%.
- For aluminium, 0.90% and -0.86%
- For copper, 1.11% and -0.92%

[8] Only statistically significant values are considered; only observations with a t-value of 2 or above are considered

[9] See table 1A in the appendix for estimations for the complete sample, including all securities, for an example

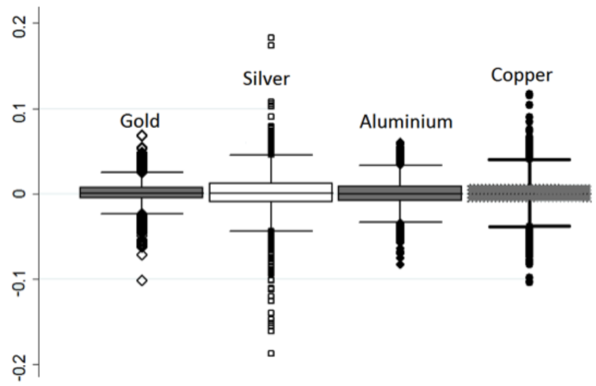
4.5 Corrections for outliers and missing data

As can be expected when dealing with real-world data, there are some issues with outliers, missing values and other impurities and irregularities in the data. We employ a number of methods to adjust for this.

4.5.1 Adjusting for extreme outliers

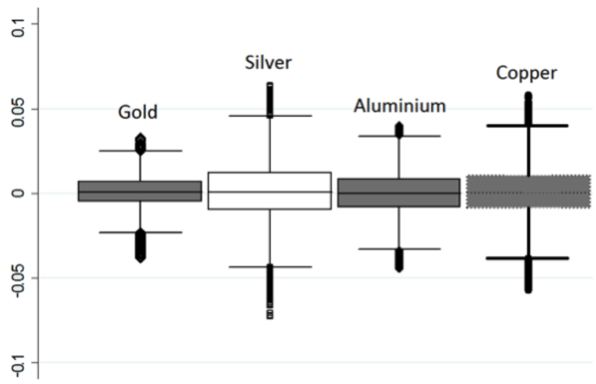
To prevent extreme outliers from influencing our results too much, we winsorise the top and bottom 1% of daily differences in commodity prices. The box plots below, figure 1 and figure 2, illustrate the effect this has on our data. One can clearly see that it's feasible to exclude such extreme outliers for log returns, as their deviation from the rest of the sample is considerable enough to dramatically influence the estimates on particular trading days.

Figure 1: Daily commodity returns, pre-winsorization



These box plots show the distribution of the logarithm of daily changes in commodity prices, broken down by commodity. In the figure above, we see the distribution before winsorizing the top and bottom percent, and in the figure below we have the same data after wisorization. Note the difference in scale.

Figure 2: Daily commodity returns, post-winsorization



We find that some of our data hasn't been adjusted for splits or reverse stock splits. This means that a few of our firms have a few very extreme value for daily stock returns, with prices nominally increasing hundreds of percent over night. Strangely, this is usually corrected and adjusted for in the days following the actual change in shares outstanding. To eliminate these extreme outliers, we winsorize the top and bottom percent of daily stock returns, for a total of 98% winsorization.

Figure 3: Daily stock returns,
pre-winsorization

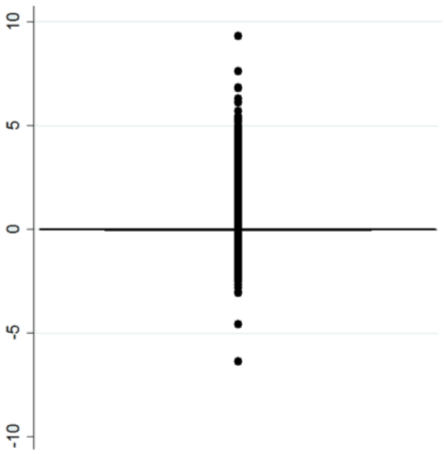
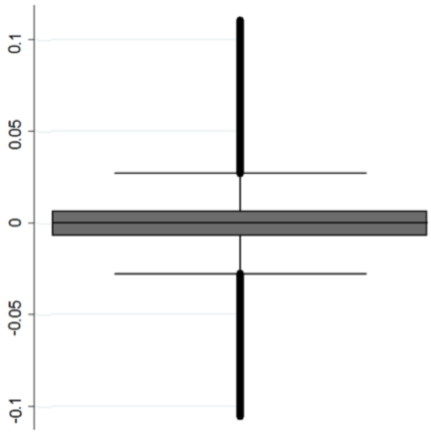


Figure 4: Daily stock returns,
post-winsorization



These box plots show the distribution of the logarithm of daily price changes in stocks. In the figure to the left, we see the distribution of daily stock reruns before winsorization. In the figure to the right, we see the same data after a 98% winsorization. Note that the scales are 2 orders of magnitude from each other, and the unreasonable extreme values before winsorization.

4.5.2 *Correcting for missing data*

In some cases, information about the number of shares outstanding is found to be missing for several days in a row. In some cases, this is also true for returns, which are highly relevant for our study. When data on number of shares outstanding or returns is missing, we carry forward the preceding values. We argue this to be the most correct method, as some of the companies are traded rarely enough for there not be any trades on a particular day, and missing prices tend to occur on such dates. We manually verify that no price is carried forward in a strange or inconsistent manner.

4.6 *Obtaining our results*

To obtain our results, we regress the logarithm of double lag, lag, daily, lead, daily value weighted average return on the daily stock returns, while using company fixed effects, clustering by unique quarter and using robust standard errors.

4.7 *The Market model*

We estimate the following market model to obtain the betas for the different commodities:

$$R_{ct} = \alpha_c + \beta_c R_{ct} + \beta_{cm} R_{mt} + \varepsilon_t$$

The two samples are first treated separately. The model estimations are executed in an identical manner for all of the different commodities and markets. Any differences in coefficients are likely to appear already at this point.

4.8 *Clustering standard errors and fixed effects*

In our model estimations, we cluster standard errors in the time dimension, by unique quarter. Due to the nature of the sample, we would expect observations within companies and within unique quarters to be similar. However, we only choose to cluster by quarter, although we perform tests where we cluster standard errors by two dimensions. The two methods are then compared. As Tufano notes, stock price exposures to gold prices vary substantially over time and between firms, and thus we decide to use firm fixed effects. Since it is likely that securities exhibit varying levels of company-specific effects, we include company fixed effects. To adjust for heteroscedasticity, we use robust standard errors.

4.9 Tests for differences

After obtaining our results for the estimations for all commodities, run separately for both samples, we test for differences in the betas across markets in two ways. Our tests is a Student's t-test, used to test equality of the mean values of the obtained coefficients. This is achieved by interacting all of the explanatory variables with a dummy variable taking on the value of 1 for observations belonging to the Scandinavian stock markets and 0 for observations belonging to the London Stock Exchange, respectively. The rest of the estimation formula remains the same, with robust standard errors, standard errors clustered in the time dimension by unique quarter and firm fixed effects. These regressions are also run separately for only the days previously defined as "event days". This is done partly as to see if this has an effect on coefficients, the observed differences between markets or significance levels, and partly as a robustness test. In its simple form, the estimation formula is as follows:

$$R_{ct} = \alpha_c + \beta_c R_{ct} + \beta_{cm} R_{mt} + \delta_{00} d + \delta_{01} d + \varepsilon_t$$

Where

R_{ct} is the logarithm of the daily return on stock c from t-1 to t

R_{mt} is the logarithm of the daily value-weighted market return from day t-1 to t for the country of listing.

δ_{00} is $beta_c R_{ct}$

δ_{01} is $beta_c m R_{mt}$

d is the dummy variable

α_c is the constant term for the regression.

ε_t is the error term for the regression.

4.10 The Efficient Market Hypothesis

A well-established and popular concept, the efficient market, as defined by Fama (1970), is of particular interest to our study. Fama describes markets as efficient in regards to information, meaning that markets and securities fully reflect all available information. Three different forms are often cited: weak-form efficiency, semi-strong form efficiency and strong-form efficiency. In weak-form efficiency, markets are assumed to reflect all historical information, and exhibit no serial correlations, meaning that security prices cannot be predicted based on historical information. Thus it is not possible to earn abnormal returns based on historical returns, at least not in the long run. In semi-strong form, markets reflect all publicly available information, and thus it is not possible to earn abnormal returns by trading on such information. Finally, in strong-form efficiency, markets reflect all available public and private information, and thus it is not possible to earn abnormal returns by trading on such information. This implies that no one can earn abnormal returns.

4.11 Multicollinearity, autocorrelation, heteroscedasticity and robustness

We need to test for some common problems in the data.
We begin by performing a test for serial correlation in the model, as discussed by Wooldridge (2002) and written by Drukker (2003); in the Wooldridge test, a Wald test is used to test the null hypothesis of no autocorrelation.

Multicollinearity tests are performed as written by Ender (2010), producing a number of collinearity diagnostics including VIF, tolerance, eigenvalues, condition index, and R-squared.

A robustness test is also performed by systematically excluding and including each of the testing variables and estimating a set of regressions on the core variables, as written by Barslund (2007). The tests are performed for each model estimation, thus testing for each of the four commodities separately, including the daily price change of the commodity and value-weighted returns as core variables.

5 RESULTS

The following section begins with a set of descriptive statistics and correlations for our dataset. The values shown in the tables indicate no major differences between the two markets. We analyze these further through the use of multiple regressions and difference testing to establish whether there is any observable or significant difference between the two markets. We then conclude the section by conducting several measures to test for robustness.

5.1 Descriptive statistics

Table 1: Cross-correlation table

This table shows the correlation between prices at a daily level for the commodities we examine.

Variables	Gold	Silver	Aluminium	Copper
Gold	1.000			
Silver	0.945	1.000		
Aluminium	0.109	0.272	1.000	
Copper	0.735	0.785	0.686	1.000

Table 2 shows the results for cross-correlations of the different commodities. The results are consistent with what has been observed in the vast literature on the correlations between commodity prices; as predicted we find a high degree of correlation between our four examined commodities.

The main descriptive statistic on the number of commodity-sensitive firms included in the market-specific datasets are shown in table 2. Generally, there is large variation in the values; the mean and maximum values are very far apart. However, the values are very similar across markets, and thus it is however difficult to draw any conclusions on the differences between markets.

Table 2: Descriptive statistics

This table shows how we categorize the firms and observations in our data as sensitive to different commodity price changes. We show this for the London Stock Exchange, the Scandinavian stock exchanges and an aggregate of the two markets. We also include mean returns for days with high commodity returns.

	Stock Exchange Location		
	London Stock Exchange	**Scandinavian Stock Exchanges**	**Total**
Number of distinct companies	6,763	2,837	9,600
% of total sample	70.4%	29.6%	100.0%
Total no. observations in sample	16,461,446	7,072,642	23,534,088
Gold companies			
Gold sensitive companies	112	17	129
% of sample	1.7%	0.6%	1.3%
Observations included			
Included	288,935	28,932	317,867
% of sample	1.8%	0.4%	1.4%
Stock return on high-return days*			
Mean stock return	0.648%	0.500%	0.634%
Max. stock return	11.00%	9.531%	11.00%
Silver companies			
Silver sensitive companies	112	17	129
% of total sample	1.7%	0.6%	1.3%
Observations included			
Included	288,935	28,932	317,867
% of sample	1.8%	0.4%	1.4%
Stock return on high-return days*			
Mean stock return	0.782%	0.622%	0.768 %
Max. stock return	9.531%	11.00%	11.00%
Aluminium companies			
Aluminium sensitive companies	139	19	157
% of total sample	2.0%	0.7%	1.6%
Observations included			
Included	297,005	60,580	357,584
% of total sample	1.8%	0.9%	1.5%
Stock return on high-return days*			
Mean stock return	1.473%	1.516 %	1.481 %
Max. stock return	9.531%	.11.00%	11.00%
Copper companies			
Copper sensitive companies	82	27	109
% of total sample	1.2%	1.0%	1.1%
Observations included			
Included	213,359	58,609	271,968
% of total sample	1.3%	0.8%	1.2%
Stock return on high-return days*			
Mean stock return	2.656%	2.110 %	2.538%
Max. stock return	9.531%	11.00%	11.00%

*High-return days are defined as the upper 5% of daily commodity returns

Figure 5: Mean stock returns for gold-sensitive companies by quartile

This figure shows mean stock returns for gold-sensitive companies on days that correspond to the upper and lower 5% of daily gold returns

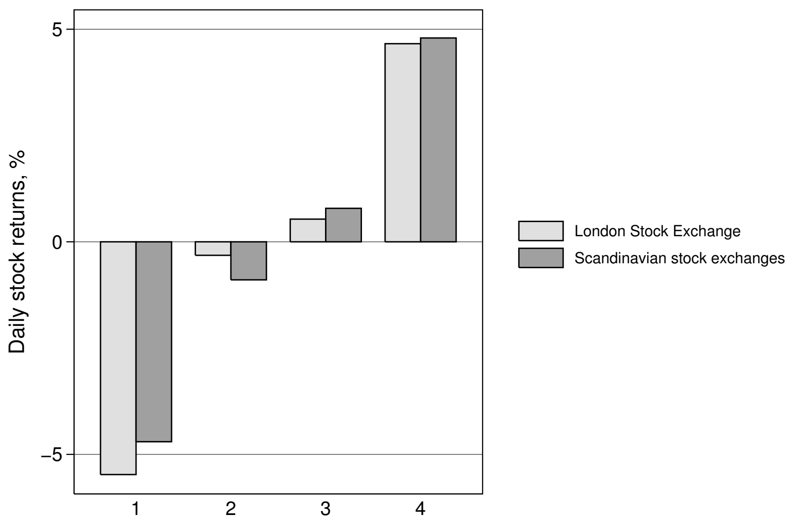


Figure 5 and figure 6 illustrate the mean stock returns on days with high commodity price changes. We observe that the sensitive groups are clearly not entirely homogeneous. Differences across stock markets are very small, although the London Stock Exchange would seem to exhibit a slightly stronger negative reaction.

Figure 6: Mean stock returns for silver-sensitive companies by quartile

This figure shows mean stock returns for silver-sensitive companies on days that correspond to the upper and lower 5% of daily silver returns

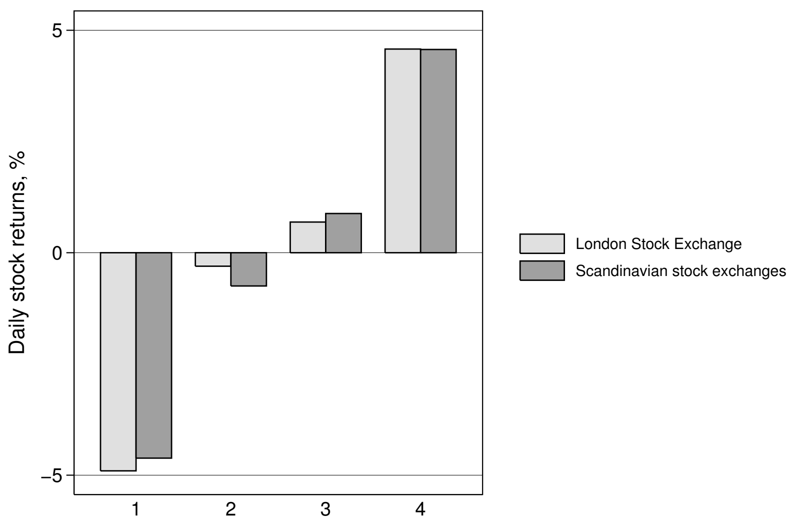


Figure 7: Mean stock returns for aluminium-sensitive companies by quartile
This figure shows mean stock returns for aluminium-sensitive companies on days that correspond to the upper and lower 5% of daily aluminium returns

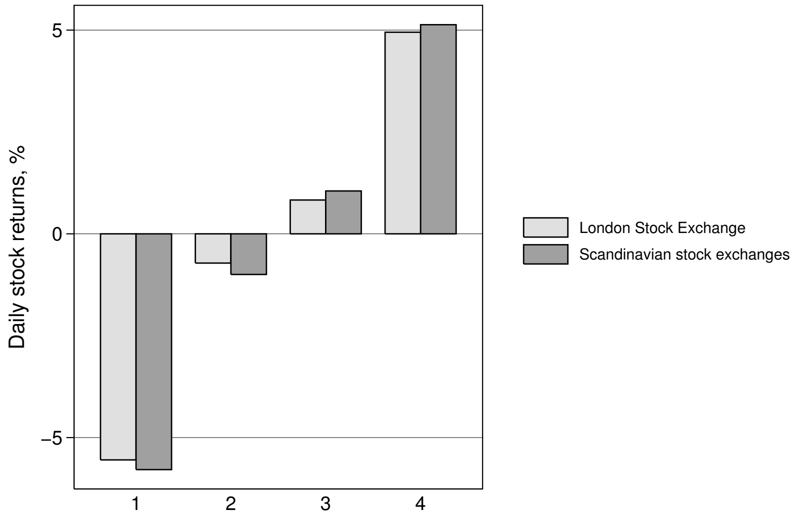


Figure 7 and figure 8 illustrate the mean stock returns on days with high commodity price changes. Once again, we observe that the groups defined as "sensitive" are not entirely homogeneous. As with gold and silver, the observed differences between the different stock markets are very small, although rather surprisingly, the Scandinavian stock exchanges would seem to exhibit a slightly stronger reaction to both positive and negative news regarding the prices of commodities.

Figure 8: Mean stock returns for copper-sensitive companies by quartile
This figure shows mean stock returns for copper-sensitive companies on days that correspond to the upper and lower 5% of daily copper returns

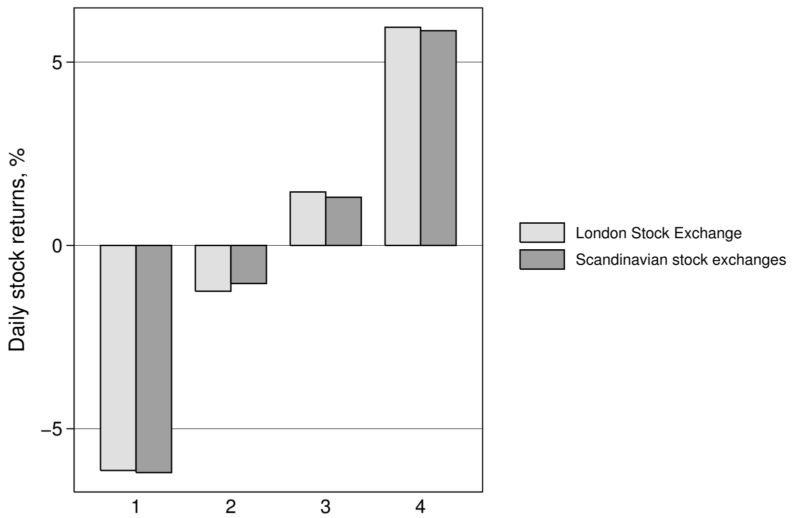


Table 3: Regression results, by market

This table shows the coefficients of daily stock returns regressed on commodity price changes for the observation period [-2;1] for the firms sensitive to the particular commodities. Value-weighted return is used as a control variable, we cluster on unique quarter and use firm fixed effects. We use robust standard errors. We report the results separately for the Scandinavian stock exchanges and the London Stock Exchange.

	Scandinavia Daily stock returns	London Stock Exchange Daily stock returns
Gold return day -2	0.0831*	0.0682**
	(2.23)	(3.35)
Gold return day -1	0.128***	0.181***
	(4.50)	(9.75)
Gold return day 0	0.230***	0.311***
	(4.36)	(10.38)
Gold return day 1	0.0199	0.0145
	(0.67)	(1.34)
Value-weighted return	0.432***	0.406***
	(7.95)	(12.63)
Constant	-0.00109	-0.00150***
	(-1.78)	(-4.65)
Observations	5033	50639
Silver return day -2	0.0345	0.0413***
	(1.57)	(3.77)
Silver return day -1	0.0794***	0.0844***
	(5.40)	(7.70)
Silver return day 0	0.151***	0.182***
	(5.67)	(15.49)
Silver return day 1	0.0337	0.0545***
	(1.72)	(6.02)
Value-weighted return	0.414***	0.375***
	(7.47)	(12.12)
Constant	-0.00101	-0.00141***
	(-1.79)	(-4.97)
Observations	5033	50639
Aluminium return day -2	0.0846*	-0.00366
	(2.38)	(-0.21)
Aluminium return day -1	0.136***	0.112***
	(5.93)	(7.19)
Aluminium return day 0	0.238***	0.238***
	(7.87)	(11.39)
Aluminium return day 1	-0.0259	0.0155
	(-1.15)	(1.24)
Value-weighted return	0.836***	0.820***
	(22.89)	(19.21)
Constant	-0.000415	-0.000451
	(-1.06)	(-1.91)
Observations	10796	50297
Copper return day -2	0.0559*	-0.00126
	(2.58)	(-0.11)
Copper return day -1	0.115***	0.115***
	(8.55)	(7.09)
Copper return day 0	0.195***	0.290***
	(6.93)	(11.55)
Copper return day 1	-0.0147	-0.000418
	(-0.65)	(-0.04)
Value-weighted return	0.813***	1.002***
	(22.47)	(18.97)
Constant	-0.000363	-0.000176
	(-1.01)	(-0.66)
Observations	10388	38215

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2 Results from the market-specific estimates

Regression results are presented in table 3. The following subsections discuss the results for each commodity in detail.

5.2.1 Gold

For both exchanges we see that all of the coefficients are significant in explaining today's stock return, except for the lead variable. As is reasonable to expect, their relative importance decreases the further back in time the price changes occur. The coefficient for the day before yesterday is approximately the same across the markets, and certainly not significantly different. The difference in coefficients for the effect of today's gold price and yesterday's gold price are more noticeable. Rather surprisingly, the effect of yesterday's gold price on today's stock prices of gold-sensitive companies would seem to be more noticeable on the London Stock Exchange than on the Scandinavian stock exchanges. However, if we see the sum of the lagged variables as a proportion of the sum of the lagged coefficients and today's coefficient, we find that older prices are proportionately more important for Scandinavian firms. That the London Stock Exchange has a larger absolute value for total exposure during the three-day event- and pre-event observation period is not surprising, as the average gold exposure of gold companies on the London Stock Exchange is higher than that of similar firms on the Scandinavian stock exchanges.[10] Since they are statistically different, it is reasonable to check the proportions of explanatory power that comes from the lagged variables:

Scandinavia

$$\frac{Return[-2]+Return[-1]}{Return[-2]+Return[-1]+Return[0]} = \frac{0.0831+0.1280}{0.08306+0.1280+0.2302} \approx 0.4783$$

London

$$\frac{0.0682+0.1815}{0.0682+0.1815+0.3112} \approx 0.4452$$

[10] This is an interesting notion, but unfortunately beyond the scope of this thesis

This gives us a rough indication of how, when predicting the stock prices of gold companies, the explanatory power of the lagged variables is slightly larger on the Scandinavian stock exchanges than on the London Stock Exchange.

5.2.2 Silver

Silver behaves very similarly across the different markets. The differences are small throughout, and none of these are likely to be statistically significant. The relative importance of the lagged variables decreases with the relative distance from today, as expected. In contrast to what can be observed in regards to gold, and the Scandinavian stock exchanges, the lead term is statistically significant, although the effect is rather small. The difference for individual coefficients is formally tested in the next section.

5.2.3 Aluminium

The results for aluminium are extremely similar across both markets in terms of today's and yesterday's price changes. However, we observe a significant difference in the coefficient for the second lag term. This difference would seem to point towards a bias, with the Scandinavian stock exchanges exhibiting a positive effect from the commodity price changes from two days before, and the London Stock Exchange exhibiting an effect that is essentially zero.

5.2.4 *Copper*

The Scandinavian stock exchanges exhibit the same apparent bias for copper as they do for aluminium. However, unlike for aluminium, there seems to be a significant difference in the effect of today's copper price, and the total effect as well. The coefficients for the first lagged variable are more or less identical both in size and significance across markets. Much like in the same way as for the gold price, we can reason that the commodity prices from the day before and the day before yesterday are proportionately more important in explaining today's stock price for the copper-sensitive companies in the Scandinavian stock exchanges than on the London Stock Exchange. Using the same calculation as before (we omit one of the variables for the London Stock Exchanges, since it is not significantly different from zero):

Scandinavia

$\frac{0.0559+0.1147}{0.0559+0.1147+0.1948} \approx 0.4669$

London

$\frac{0.1148}{0.1148+0.2904} \approx 0.2834$

The proportion difference is larger than than for gold and substantial.

5.3 *Results from difference testing*

Although the results from the separate estimations already provide some information on the differences and similarities in reactions across markets, they alone are not sufficient for us to determine whether there is an observable difference, and thus we conduct tests for the differences in the coefficients' means. We use a Student's t-test, which is appropriate given the reasonable assumption of normal distribution. Given that the assumption of normality holds, the test should have greater efficiency than other comparable tests. We run the same test for two samples: first the complete sample, and then a limited sample, including only days previously defined as "event days", thus excluding the middle 50% of observations. Given its nature, the latter test also partly serves as a robustness test.

Again, we comment our results one commodity at a time. The results for the regressions are presented in table 4.

Table 4: Difference testing results

This table shows the coefficients for daily stock returns regressed on commodity price changes for the observation period [-2;1] for firms sensitive to a particular commodity price. Value-weighted return is used as a control variables for the firms sensitive to a particular commodity. We cluster on unique quarter and use firm fixed effects and use robust standard errors. We also include all these variables interacted with a dummy variable which is 1 for the Scandinavian Stock Exchanges, thus giving us a value for the size of the difference between markets, and the significance of the difference. The left column in both figures shows the results for all daily commodity price changes, and the right column shows the results for only the top and bottom 25% of daily commodity price changes.

	Complete sample Daily stock returns	Excluding zero-return days Daily stock returns
Gold return, day -2	0.0678**	0.0945***
	(3.33)	(3.80)
Gold return day -1	0.181***	0.187***
	(9.79)	(8.38)
Gold return day 0	0.311***	0.310***
	(10.38)	(10.01)
Value-weighted return	0.407***	0.399***
	(12.64)	(10.80)
Difference in Gold return, day -2	0.0152	-0.0357
	(0.41)	(-0.58)
Difference in Gold return day -1	-0.0533	-0.00985
	(-1.71)	(-0.27)
Difference in Gold return day 0	-0.0808	-0.0783
	(-1.95)	(-1.75)
Difference in Gold return day 1	0.0199	0.0604
	(0.67)	(1.47)
Difference in value-weighted return	0.0256	0.0161
	(0.57)	(0.36)
Constant	-0.00145***	-0.00160***
	(-4.36)	(-3.74)
Observations	55672	28258

	Complete sample Daily stock returns	Excluding zero-return days Daily stock returns
Silver return, day -2	0.0412***	0.0471**
	(3.59)	(3.11)
Silver return day -1	0.0841***	0.0827***
	(7.73)	(5.70)
Silver return day 0	0.177***	0.172***
	(15.52)	(15.47)
Value-weighted return	0.389***	0.417***
	(12.16)	(10.11)
Difference in Silver return, day -2	-0.00667	-0.0253
	(-0.25)	(-0.74)
Difference in Silver return day -1	-0.00466	-0.00597
	(-0.28)	(-0.24)
Difference in Silver return day 0	-0.0260	-0.0225
	(-1.02)	(-0.87)
Difference in Silver return day 1	0.0337	0.0378
	(1.73)	(1.55)
Difference in value-weighted return	0.0244	0.0247
	(0.49)	(0.52)
Constant	-0.00133***	-0.00139***
	(-4.42)	(-3.75)
Observations	55672	28899

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Complete sample Daily stock returns	Excluding zero-return days Daily stock returns
Aluminium return, day -2	-0.00394	-0.0107
	(-0.23)	(-0.57)
Aluminium return day -1	0.112***	0.106***
	(7.20)	(5.79)
Aluminium return day 0	0.238***	0.225***
	(11.46)	(12.40)
Value-weighted return	0.819***	0.870***
	(19.17)	(20.12)
Difference in Aluminium return, day -2	0.0885**	0.0890**
	(3.53)	(2.77)
Difference in Aluminium return day -1	0.0243	0.0133
	(1.27)	(0.51)
Difference in Aluminium return day 0	-0.000248	0.000974
	(-0.01)	(0.03)
Difference in Aluminium return day 1	-0.0259	-0.0193
	(-1.15)	(-0.71)
Difference in value-weighted return	0.0162	0.00491
	(0.34)	(0.11)
Constant	-0.000443	-0.000691*
	(-1.91)	(-2.40)
Observations	55672	28258

	Complete sample Daily stock returns	Excluding zero-return days Daily stock returns
Copper return, day -2	-0.00125	0.00146
	(-0.11)	(0.08)
Copper return day -1	0.115***	0.102***
	(7.12)	(5.48)
Copper return day 0	0.290***	0.285***
	(11.60)	(12.60)
Value-weighted return	1.002***	1.010***
	(18.97)	(19.32)
Difference in Copper return, day -2	0.0572**	0.0451
	(2.78)	(1.85)
Difference in Copper return day -1	-0.000144	-0.00749
	(-0.01)	(-0.36)
Difference in Copper return day 0	-0.0957*	-0.0899*
	(-2.42)	(-2.22)
Difference in Copper return day 1	-0.0147	-0.0139
	(-0.65)	(-0.44)
Difference in value-weighted return	-0.189**	-0.199**
	(-3.16)	(-2.89)
Constant	-0.000216	-0.000409
	(-0.93)	(-1.21)
Observations	48603	25272

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.3.1 Gold

None of the differences in coefficient means across the models are statistically significant at the 5% level, implying that there are no statistically significant differences between the different markets. However, the estimated difference in today's coefficient is significant on the 10% level, with the first lagged variable also showing some significance.

5.3.2 Silver

As our preliminary observations on the first estimations seemed to indicate, there is no apparent difference in reactions between markets. Generally, the significance levels are low, and the estimated difference coefficients have very low values.

5.3.3 Aluminium

The cross-model difference test estimates exhibit an expected pattern, confirming what the first, market-specific, estimations seem to indicate. Only the difference coefficient for the second lag term is significantly different between markets.

5.3.4 Copper

The estimated differences between markets show significance for today's copper price (on the 1% level) and for the second lag term (on the 5% level). The difference tests confirm the the indicated difference the market-specific estimates.

5.3.5 Comparison between the complete and limited sample

As previously described, we also run the same regressions while excluding the middle 50% of daily commodity price changes. This 50% is highly concentrated around zero, accounting for roughly 25% of the total range in returns. The results from these estimations are very similar to the ones with the complete sample

5.4 Robustness tests

Apart from the previously described regressions on the limited sample, we also conduct a series of robustness tests. The Wooldridge test for serial correlation within panels includes a Wald test to test the null hypothesis of no serial correlation. The test returns F-values that are sufficiently low for us not to reject the null hypothesis.

We perform various collinearity tests. None of the calculated collinearity diagnostics point towards any problems with multicollinearity in the data.

We also check for robustness of the data by systematically excluding and including each of the testing variables and estimating a set of regressions on the core variables. The tests are performed for each model estimation, thus testing for each of the four commodities separately, always including the daily price change of the commodity and value-weighted returns as core variables.

Apart from these tests, we re-do our difference estimations by clustering standard errors by two dimensions: not only time (unique quarter) but also on the firm level. The regressions do not include firm fixed effects. The results do not differ significantly from our main estimates.

From the above tests we conclude that there are no significant issues with the data included in the model estimates. All of the above test results are included in the appendix.

6 CONCLUSIONS AND IMPLICATIONS

6.1 conclusions

We have examined three different hypotheses regarding differences in market efficiency, information diffusion and the speed at which commodity price information is implemented in stock prices across different markets. By analyzing stock and commodity price information, we have studied whether there is a quantitative difference in the reaction to commodity prices, whether the markets exhibit differing qualitative reactions and whether it would be possible to earn abnormal returns by trading on commodity price information.

The observed effects, and the differences in particular, are generally of high significance, but of limited magnitude. Although we observe some differences in the proportionate effects of the lagged variables in regard to the effect of today's commodity price, particularly for gold and copper, these differences in particular are hard to generalize. We fail to see a predictable pattern that could be generalized across markets or commodities, thus the estimation results can only be seen to apply for the specific commodities and markets.

On average, however, we would seem to have one rather weak indicator for each commodity suggesting that the Scandinavian stock exchanges might exhibit slightly slower reactions and of lower magnitude. These indicators are inconsistent between commodities and many are only barely statistically significant on the 5% level.

An important point to note is that generally, stock markets seem to follow each other, and the New York Stock Exchange in particular; as noted by Eun et al. (1989), no single stock market has any noticeable effect on the global market, except for the NYSE, which exhibits a strong tendency to lead the global market. We cannot rule out the possibility of both of our included markets exhibiting a stronger tendency to follow the NYSE, rather than the prices of commodities.

By observing differences in reactions to commodity pricing information, we reject the null hypothesis of different markets exhibiting a similar or identical total reaction to commodity price changes. We are, however, unable to reject the second null hypothesis, as the results are mixed and inconclusive; this is also true for the third null hypothesis, as it would not appear possible to benefit from a potential arbitrage opportunity and earn abnormal returns based on commodity price information alone. We therefore find evidence that supports both the weak and semi-strong form of the efficient market hypothesis.

6.2 Limitations and suggestions for further research

As noted previously, a large amount of the reaction to new information occurs within minutes, or at most a few hours. We are unable to determine whether the Scandinavian Stock Markets react differently, although our estimates seem to point in such direction. The inclusion of data of higher frequency would warrant further research on the topic, but require significantly larger computational resources, time and better data access. To further increase significance and reduce standard errors, including other smaller stock exchanges would be a viable option.

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APPENDIX

Table A.1: Market returns

This table shows the coefficients for daily stock returns regressed on commodity price changes for the observation period [-2;1] for all firms in the dataset for all commodities. We use value-weighted returns as a control variable, firm fixed effects and cluster by unique quarter. We use robust standard errors. We present the coefficients separately for the Scandinavian exchanges and the London Stock Exchange.

	Scandinavia Daily stock returns	London Stock Exchange Daily stock returns
Gold return, day -2	0.00171	0.00380
	(0.26)	(0.63)
Gold return day -1	0.00195	0.0176
	(0.23)	(1.68)
Gold return day 0	0.00484	0.0244**
	(0.45)	(2.75)
Gold return day 1	0.00235	-0.00452
	(0.32)	(-0.97)
Value-weighted return	0.519***	0.424***
	(21.32)	(41.95)
Constant	-0.000340	-0.000457*
	(-1.76)	(-2.50)
Observations	1258682	2928438
Silver return, day -2	0.0150***	0.0121*
	(3.64)	(2.66)
Silver return day -1	0.00763*	0.0136**
	(2.09)	(2.81)
Silver return day 0	0.0232***	0.0259***
	(4.22)	(4.53)
Silver return day 1	0.00740	0.00490*
	(1.86)	(2.08)
Value-weighted return	0.514***	0.418***
	(21.33)	(40.38)
Constant	-0.000376	-0.000476*
	(-1.98)	(-2.65)
Observations	1258682	2928438
Aluminium return, day -2	0.0205*	0.0220*
	(2.25)	(2.66)
Aluminium return day -1	0.0368***	0.0505***
	(4.56)	(6.35)
Aluminium return day 0	0.0437***	0.0237***
	(4.44)	(4.61)
Aluminium return day 1	0.00190	0.00443
	(0.35)	(1.01)
Value-weighted return	0.505***	0.416***
	(20.05)	(40.42)
Constant	-0.000347	-0.000443**
	(-1.97)	(-2.70)
Observations	1258682	2928438
Copper return, day -2	0.0184*	0.0179**
	(2.20)	(2.75)
Copper return day -1	0.0375***	0.0453***
	(5.09)	(6.78)
Copper return day 0	0.0437***	0.0214***
	(4.83)	(5.23)
Copper return day 1	0.000998	0.00148
	(0.28)	(0.36)
Value-weighted return	0.496***	0.411***
	(20.17)	(36.94)
Constant	-0.000390*	-0.000480**
	(-2.27)	(-2.91)
Observations	1258682	2928438

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The tables A.2 through A.5 show the results for robustness testing. The tests systematically excludes and includes each of the testing variables and estimates a set of regressions on the core variables.

Table A.2: Robustness tests

Core variables	Max	Min	Mean	Average Standard Deviation	PercSigni	Perc+	Perc-	Average T-value	Obs
Gold return day 0	0.2894	0.2871	0.2883	0.0192	1	1	0	15.039	8
Value-weighted return	0.7050	0.7017	0.7034	0.0257	1	1	0	27.367	8
Target variables	Max	Min	Mean	AvgSTD	PercSigni	Perc+	Perc-	AvgT	Obs
Gold return day -2	0.0465	0.0442	0.0453	0.0168	1	1	0	2.703	4
Gold return day -1	0.1248	0.1234	0.1241	0.0157	1	1	0	7.884	4
Gold return day 1	0.0194	0.0174	0.0184	0.0119	0	1	0	1.551	4

Table A.3: Robustness tests

Core variables	Max	Min	Mean	Average Standard Deviation	PercSigni	Perc+	Perc-	Average T-value	Obs
Silver return day 0	0.1618	0.1570	0.1593	0.0088	1	1	0	18.155	8
Value-weighted return	0.6899	0.6886	0.6892	0.0250	1	1	0	27.596	8
Target variables	Max	Min	Mean	AvgSTD	PercSigni	Perc+	Perc-	AvgT	Obs
Silver return day -2	0.0319	0.0273	0.0296	0.0088	1	1	0	3.372	4
Silver return day -1	0.0595	0.0568	0.0581	0.0074	1	1	0		4
Silver return day 1	0.0227	0.0167	0.0196	0.0116	0.25	1	0	1.693	4

Table A.4: Robustness tests

Core variables	Max	Min	Mean	Average Standard Deviation	PercSigni	Perc+	Perc-	Average T-value	Obs
Aluminium return day 0	0.1784	0.1756	0.1770	0.0134	1	1	0	13.179	8
Value-weighted return	0.6509	0.6461	0.6485	0.0267	1	1	0	24.323	8
Target variables	Max	Min	Mean	AvgSTD	PercSigni	Perc+	Perc-	AvgT	Obs
Aluminium return day -2	0.0291	0.0248	0.0270	0.0142	0.50	1	0	1.899	4
Aluminium return day -1	0.1166	0.1153	0.1159	0.0143	1	1	0	8.133	4
Aluminium return day 1	0.0020	0.0014	0.0016	0.0118	0	1	0	0.138	4

Table A.5: Robustness tests

Core variables	Max	Min	Mean	Average Standard Deviation	PercSigni	Perc+	Perc-	Average T-value	Obs
Copper return day 0	0.1615	0.1544	0.1580	0.0137	1	1	0	11.506	8
Value-weighted return	0.6152	0.6133	0.6142	0.0269	1	1	0	22.804	8
Target variables	Max	Min	Mean	AvgSTD	PercSigni	Perc+	Perc-	AvgT	Obs
Copper return day -2	0.0246	0.0185	0.0216	0.0100	0.50	1	0	2.169	4
Copper return day -1	0.1147	0.1131	0.1139	0.0105	1	1	0	10.878	4
Copper return day 1	0.0014	-0.0001	0.0007	0.0062	0	0.75	0.25	0.117	4

Table A.6: Wooldridge tests for serial correlation

The table shows the results for the Wooldridge test for each of the commodity regressions.
A Wald test is used to test for the null hypothesis.
H_0 : No serial correlation within panels

Variables	Scandinavian Stock Exchanges
Gold, F(1, 2)	2.484
Probability>F	0.255
Silver, F(1, 2)	2.318
Probability>F	0.267
Aluminium, F(1, 4)	0.650
Probability>F	0.465
Copper, F(1, 4)	0.113
Probability>F	0.754

Variables	London Stock Exchange
Gold, F(1, 25)	0.006
Probability>F	0.937
Silver, F(1, 25)	0.054
Probability>F	0.817
Aluminium, F(1, 24)	0.713
Probability>F	0.406
Copper, F(1, 16)	0.091
Probability>F	0.766

Table A.7: Collinearity tests

The table shows the results for collinearity tests for each of the regressions used in the difference tests. The results indicate no observable multicollinearity.

Variable	VIF	VIF, Square root	Tolerance	R-Squared
Gold return day -2	1.15	1.07	0.8699	0.1301
Gold return day -1	1.15	1.07	0.8701	0.1299
Gold return day 0	1.16	1.08	0.8636	0.1364
Gold return day 1	1.15	1.07	0.8695	0.1305
Value-weighted return	1.25	1.12	0.7971	0.2029
Difference in Gold return, day -2	1.15	1.07	0.8699	0.1301
Difference in Gold return, day -1	1.15	1.07	0.8702	0.1298
Difference in Gold return, day 0	1.16	1.08	0.8642	0.1358
Difference in Gold return, day 1	1.15	1.07	0.8694	0.1306
Difference in value-weighted return	1.25	1.12	0.7978	0.2022
Mean VIF	1.17			
Silver return day -2	1.15	1.07	0.8661	0.1339
Silver return day -1	1.16	1.08	0.8617	0.1383
Silver return day 0	1.18	1.09	0.8439	0.1561
Silver return day 1	1.17	1.08	0.8514	0.1486
Value-weighted return	1.29	1.13	0.7766	0.2234
Difference in Silver return, day -2	1.16	1.07	0.8658	0.1342
Difference in Silver return, day -1	1.16	1.08	0.8610	0.1390
Difference in Silver return, day 0	1.19	1.09	0.8434	0.1566
Difference in Silver return, day 1	1.17	1.08	0.8530	0.1470
Difference in value-weighted return	1.28	1.13	0.7782	0.2218
Mean VIF	1.19			
Aluminium return day -2	1.15	1.07	0.8693	0.1307
Aluminium return day -1	1.15	1.07	0.8676	0.1324
Aluminium return day 0	1.36	1.16	0.7375	0.2625
Aluminium return day -1	1.15	1.07	0.8687	0.1313
Value-weighted return	1.47	1.21	0.6809	0.3191
Difference in Aluminum return, day -2	1.15	1.07	0.8692	0.1308
Difference in Aluminum return, day -1	1.15	1.07	0.8685	0.1315
Difference in Aluminum return, day 0	1.33	1.15	0.7547	0.2453
Difference in Aluminum return, day 1	1.15	1.07	0.8685	0.1315
Difference in value-weighted return	1.44	1.20	0.6962	0.3038
Mean VIF	1.25			
Copper return day -2	1.15	1.07	0.8685	0.1315
Copper return day -1	1.15	1.07	0.8663	0.1337
Copper return day 0	1.52	1.23	0.6588	0.3412
Copper return day 1	1.15	1.07	0.8660	0.1340
Value-weighted return	1.64	1.28	0.6083	0.3917
Difference in Copper return, day -2	1.15	1.07	0.8677	0.1323
Difference in Copper return, day -1	1.16	1.08	0.8653	0.1347
Difference in Copper return, day 0	1.46	1.21	0.6829	0.3171
Difference in Copper return, day 1	1.16	1.08	0.8649	0.1351
Difference in value-weighted return	1.59	1.26	0.6290	0.3710
Mean VIF	1.31			

Table A.8: Table caption

This table shows the coefficients for daily stock returns regressed on commodity price changes for the observation period [-2;1] for firms that are sensitive to price changes in a particular commodity. Value-weighted return is used as a control variables for the firms sensitive to a particular commodity. We also include all these variables interacted with a dummy variable which is 1 for the Scandinavian Stock Exchanges, thus giving us a value for the size of the difference between markets, and the significance of the difference. We cluster on unique quarter *and* company.

(1)

	Daily stock returns
Gold return, day -2	0.0677*** (3.41)
Gold return day -1	0.181*** (7.36)
Gold return day 0	0.311*** (4.66)
Value-weighted return	0.407*** (7.30)
Difference in Gold return, day -2	0.0154 (.)
Difference in Gold return day -1	-0.0532*** (-5.69)
Difference in Gold return day 0	-0.0807 (-1.36)
Difference in Gold return day 1	0.0200 (0.88)
Difference in value-weighted return	0.0257 (0.36)
Constant	-0.00149*** (-3.86)
Observations	55672
Silver return, day -2	0.0411*** (3.72)
Silver return day -1	0.0840*** (7.18)
Silver return day 0	0.177*** (7.85)
Value-weighted return	0.389*** (7.06)
Difference in Silver return, day -2	-0.00612 (-0.28)
Difference in Silver return day -1	-0.00408 (-0.58)
Difference in Silver return day 0	-0.0254 (-1.07)
Difference in Silver return day 1	0.0342 (1.85)
Difference in value-weighted return	0.0244 (0.32)
Constant	-0.00133*** (-3.64)
Observations	55672

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(2)

	Daily stock returns
Aluminium return, day -2	-0.00363 (-0.22)
Aluminium return day -1	0.112*** (5.88)
Aluminium return day 0	0.238*** (8.01)
Value-weighted return	0.819*** (8.39)
Difference in Aluminium return, day -2	0.0883*** (5.63)
Difference in Aluminium return day -1	0.0241 (1.41)
Difference in Aluminium return day 0	-0.000476 (-0.01)
Difference in Aluminium return day 1	-0.0259* (-2.20)
Difference in value-weighted return	0.0162 (0.10)
Constant	-0.000443 (-1.61)
Observations	61093
Copper return, day -2	-0.00106 (-0.10)
Copper return day -1	0.115*** (5.49)
Copper return day 0	0.291*** (8.38)
Value-weighted return	1.002*** (10.06)
Difference in Copper return, day -2	0.0566*** (6.13)
Difference in Copper return day -1	-0.000675 (-0.04)
Difference in Copper return day 0	-0.0963 (-1.65)
Difference in Copper return day 1	-0.0150 (-0.84)
Difference in value-weighted return	-0.189 (-1.17)
Constant	-0.000216 (-0.90)
Observations	48603

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$