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Do Commodities Lead Stock Market Industries?

Master Thesis

by
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MSc Finance

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ABSTRACT

This paper investigates whether the price changes in commodity futures can predict the stock price movements in US industries. Our estimated risk premia indicate that a large number of commodity futures do lead specific industry returns with up to five months of lag, suggesting that relevant information only gradually diffuses from commodities to relevant industries. Furthermore, we find that exploitative trading strategies that trade on the identified anomalies do not generate any abnormal returns, suggesting that the anomalies are efficiently eliminated from the market.

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1 Introduction

The limited cognitive ability of humans to process information is a fundamental and well-explored phenomenon within the field of psychology. For the financial markets, with immense amounts of continuous information that can impact asset prices, this psychological observation of limited attention and information processing has long been an important counter-argument to the school of efficient capital markets. Given its contradiction to the classical thought that all information is efficiently priced into the market at the time of availability, the limit of attention is a vast branch of empirical research within finance and economics. Commonly referred to as gradual information diffusion, it is postulated that excessive amounts of information and limited attention cause relevant information to only gradually reach all investors and, thus, only gradually be reflected in prices. Consequently, situations should arise where some asset prices reflect the information before others, causing a lead-lag relationship and a potential predictive nature in price changes over time. Indeed, a large body of literature finds evidence of these lead-lag relations, with supplier industries found to lead consumer industries (Menzly and Ozbas, 2010) and various industries found to lead the broader market (Torous et al., 2007). Furthermore, evidence of the postulated gradual information diffusion is also identified across asset classes, both in option volumes leading equity markets (Pan and Poteshman, 2006), and in various commodity futures doing the same (Narayan and Sharma, 2011; Wang et al., 2019; Jacobsen et al., 2019).

Building on the identified predictive power in supply chains and the leading nature of commodities, this paper aims to further develop the understanding of gradual information diffusion in financial markets by examining the predictive power of a vast set of commodity futures on specific industry returns. By incorporating a large set of commodity futures and distinguishing between industry sectors, this paper will contribute to the existing body of literature in two ways. Firstly, a test of the predictive relationship between a specific commodity and an industry will build on the identified lead-lag relationship within a supply chain by investigating if commodity prices, which must be intuitively reasoned to be at the top of most supply chains, portray a predictive nature. Our paper will thus investigate a potential preceding step in the gradual information diffusion process. Furthermore, our paper will dissect the identified predictive power of commodities on the broad market and aim to identify which market segments are affected. Given that both commodities and industry portfolios are identified to lead the market, our paper will offer a valuable decomposition that will help bridge the understanding between the two observations. Below, we formalise our main research question.

Do price changes in commodity futures predict future changes in industry equity returns?

Predictive power in financial markets is not only a statistical observation but also a powerful tool in trading and obtaining superior returns. With our paper examining a wide range of lead-lag relations from commodity futures to equities, our analysis also provides an ample opportunity to test if a general strategy rooted in the predictive nature of commodity futures can perform in the market. Again, efficient markets imply that any predictive nature should be eliminated, as it offers an arbitrage opportunity for investors. Testing the performance of a general trading approach founded on the predictive nature of commodities will thus offer insight into the effectiveness of the market and the potential limits to arbitrage trading, as suggested by Shleifer and Vishny, 1997. Again, we formalise our secondary research question below.

Does the predictive nature of commodity futures allow for abnormal returns to be generated in trading, suggesting inefficient markets and limits to arbitrage?

Our paper will proceed in the following manner. Firstly, a literature review is presented in Section 2 to outline the empirical framework in which this thesis is constructed. Section 3 will introduce the methodology utilised for our predictive tests and the performance test of general trading strategies, while Section 4 will detail all data being utilised for our analyses. Section 5 presents and discusses the results of our predictability test and the performance of the general trading strategies. Lastly, our conclusions and ending remarks are given in Section 6.

2 Literature Review and Theory

The limits of the human mind to obtain vast amounts of information is not only an intuitively reasonable statement but an extensive literature within psychology. As explained by Daniel Kahneman, the effort can contribute to better attention (Kahneman, 1973). However, attention is a limited resource, and the cognitive capability will have severe limitations in pushed situations (Pashler and Johnston, 1998). Excessive amounts of information beyond the attention capacity will, thus, lead to inferential errors, as the agent fails to utilise all available information accordingly (Nisbett and Ross, 1980). For a colossal and complex financial market, with vast amounts of information produced daily, it is thus firm psychological arguments that sharply contrast the idea of perfectly informed or rational investors, formally known as the efficient market hypothesis. The idea of the abovementioned cognitive imperfection in the market is extensively adapted to the realm of economics and finance and modifies the strict assumptions of the rational investor to a looser, more realistic, boundedly rational investor (Sims, 2003; Shiller, 2000).

The focus of this paper is to investigate the imperfections in the market postulated to arise from the limited information capacity of every single investor. More specifically, we will build on the literature of Merton, 1987, Hong and Stein, 1999, and Peng and Xiong, 2006, which all develop models for the implications of the cognitive information processing limitation. Firstly, a static model is developed by Merton, where investors only possess information on a limited number of stocks within a more considerable investment universe. The resulting effect is that stocks with a more significant number of investors possess information that will be held by more investors and thus be priced more correctly. On the contrary, the overlooked stocks will be held by a smaller investor base and consequently trade at a more notable discount due to lower risk-sharing. Secondly, a dynamic model for the diffusion of information in a single stock is developed by Hong and Stein, 1999. In the model, investors only gradually obtain relevant information about the stock and fail to utilise the rational expectation trick of extracting information directly from the stock price, resulting from limited attention capacity. The effect is an underreaction in the stock price when new relevant information first becomes public, and there is predictability in the stock's future returns. Lastly, and of great importance to this thesis, Peng and Xiong, 2006, challenge the efficient market assumption that new information is instantly distilled by markets and, thus, also that markets provide the best estimates regarding asset values. Their research argues that, in reality, this process requires representative investors to pay close attention when processing new information and when incorporating the newly acquired knowledge in their investment decisions. Hence, the paper suggests that investor attention may be an essential factor influencing asset prices. Considering Kahneman's (1973) classification of attention as a scarce cognitive resource, paying close attention to one piece of information arguably prevents the investor from allocating cognitive resources to other vital pieces of information. In order to study the effects of investors' attention constraint/allocation on price dynamics, Peng and Xiong develop a model that postulates the tendency of investors' limited attention leading to category learning. In other words, investors focus on a market segment rather than single stocks when faced with excessive amounts of information. Focusing on a market segment rather than firm-specific information may lead to increased correlation in returns of assets in that segment. In severe cases of category-learning, the return correlation can be even more significant than the firm's fundamental correlations. What can be drawn from this research is that category-learning, resulting from limited attention, causes gradual information diffusion, ultimately affecting the price dynamics of assets. The gradual information diffusion causes asset prices to gradually reflect all public information, as information is only reflected in asset prices once investors pay attention to it. Hence, cross-predictability of returns may be possible in correlated sectors where one of them is more efficient in terms of information processing.

This paper is related to a large body of literature on the lead-lag relations among stocks and other conventional asset classes, postulated to originate in the gradual, imperfect diffusion of information. Ignited by the influential empirical finding that returns of large stocks tend to lead those of smaller stocks (Lo and MacKinlay, 1990), academics have rationalised and further investigated the existence of the lead-lag relation in the financial markets. On the rationale of the finding, stocks with both greater analyst coverage (Brennan et al., 1993) and a more significant share of institutional investors (Badrinath et al., 1995) are found to lead their less scrutinised counterparts. These findings are linked to the effect of specialising agents in institutional investors and analysts, leading to a more efficient information processing ability and thus a quicker reaction to new information. In addition, analyst coverage and institutional ownership usually are more prevalent in stocks with a loftier market share. Furthermore, the big-to-small lead-lag effect is found to be greater within neglected industries when examining intra-industry lead-lag relations (Hou, 2007), postulating that the market does not process all information equally. Moreover, empirical findings suggest that larger firms' lead effect is primarily caused by quicker standardised factor information (Jegadeesh and Titman, 1995). However, the authors highlight that a minimal margin of any potential strategy profit can be attributed to a lead-lag effect and instead should be attributed to a stock price overreaction to new information. Moreover, Boudoukh et al., 1994, found own-autocorrelation to be the main contributor in explaining the lead effect of large stocks, discrediting the existence of predictability across stocks, referred to as cross-predictability.

Since 1990, several influential empirical studies have identified the lead-lag relationship. For example, Torous et al., 2007, identify that the monthly returns of various US industries lead the market returns by up to two months. Further, the authors identify that the predictive power of these industries also seems to lead to various established indicators of economic activity, suggesting that also important macroeconomic information diffuses slowly across the market. Moreover, the paper identifies the same cross-predictability in the eight largest stock markets outside the US. For this thesis, the abovementioned paper brings essential insight, as it identifies slow information diffusion in relation to significant macroeconomic indicators and the total stock market. It also indicates that assets with correlated payoffs can lead or lag each other's returns due to significant information gradually diffusing into the market from its origin. Indeed this is also what is found when examining the cross-predictability of economically linked firms, where the returns of a buying firm lag those of a producing firm (Cohen and Frazzini, 2008). The same relation is found when investigating supply-chains and economically related consumer and supplier industries (Menzly and Ozbas, 2010). Moreover, the latter authors identify reduced cross-predictability in supply chains with greater analyst coverage, again pointing to the immense effects of information accessibility in the financial markets.

The cross-predictability discussed in the above paragraph is the rationale that firm-relevant information only gradually reaches all affected parties, starting from upstream firms and flowing downstream. However, the discussed literature only considers an investment opportunity set of stocks. The trivial result is that the earliest observation of new information must be seen in stock returns before it diffuses downwards. This thesis aims to expand the existing framework of the equity market and investigate if information diffusion occurs before relevant information reaches the top of industry supply chains.

While the scope of this thesis is to investigate the relation between commodity futures and the equity market, interesting empirical research lies in the relationship between all asset classes. Examples are fixed income and equities or the relation between options and equities. For the latter, available research already identifies the predictive power of option volumes on equities (Pan and Poteshman, 2006).

Commodity futures and their ability to predict future returns in equities is not a new branch in finance. A substantial body of literature already documents the close economic link between raw materials and equity markets. As is also intuitively evident, the trade of commodities carries informative information about the future economic activity and pricing of assets (Grossman, 1977; Hong and Yogo, 2012). More specifically, commodity prices are linked to macroeconomic factors and variables (Barsky and Kilian, 2004) and function as a predominant predictor for equity risk premia (Welch and Goyal, 2008). As such, it is not surprising that empirical research has identified various lead-lag relations between commodities and equities in recent years. Oil commodities possess a predictive lead relation on the S&P500 index, in addition to various single US stocks (Narayan and Sharma, 2011; Wang et al., 2019). Moreover, the lead feature of oil commodity futures has been present for much of the history of traded oil (Narayan and Gupta, 2015). The same relation is also found in the Chinese equity market when analysing the effect of crude oil shocks on industries (Wong and Zhang, 2020). Furthermore, outside the commodity energy markets, futures on industrial metals, like aluminium and copper, are identified to have the same lead relation to stock markets (Jacobsen et al., 2019). Interestingly, the directional effect of industrial metals on the stock market is identified to fluctuate dependent on the macroeconomic conditions of the market, where an increase in industrial metal prices is good news (bad news) in recessions (expansions). Moreover, predictive power is also found in overnight returns of copper and soybean futures in the United States when its effects are examined on the large East Asian equity markets (Jacobsen et al., 2019).

This paper will aim to combine the informative information in commodity futures with the established literature on cross-predictability within supply chains and thus bridge the gap between two empirically proven intuitions that both suggest predictive and tradable behaviour in the financial markets. Contrary to the presented research on commodity futures, we will take a fundamental approach to analysing commodity futures as the first information stage in a supply chain. In other words, commodities will be analysed as the utmost point from which information diffuses. A recent piece of literature by Li et al., 2021 explored the exact research question presented above for the Chinese commodity futures and equity markets. The research finds that a large number of commodity futures possess predictive power over supplier and consumer stocks in the relevant supply chains when analysed daily. This thesis will further investigate these findings but differentiate itself from the abovementioned by investigating the cross-asset predictability in returns of US industries. Furthermore, we will investigate the relation using monthly data, as this is a more robust approach in empirical research.

3 Methodology

This section presents the methodology utilised to analyse the proposed predictive power of commodity futures on industry returns. To formalise the intent of the analysis, we present two main propositions. Firstly, and at the heart of the thesis, is the relation between commodity futures and industries:

Proposition 1: The cross serial return correlations between a lagged commodity future and economically affected industries ($Corr(Com_{j,t-s}, R_{i,t})$ are non-zero and can be both positive and negative dependent on the co-movement of the asset's returns. In addition, own serial correlation in the industries is zero, ($Corr(R_{i,t+1}, R_{i,t}) = 0$).

Second, as arbitrage has the potential to eliminate all gains available from the proposed cross-predictability, any finding of cross-predictability would suggest that there are limits to arbitrage trading, as postulated by Shleifer and Vishny, 1997. Thus, we form a second proposition on the limits to arbitrage.

Proposition 2: Even with arbitrage trading present in the market, there will remain some cross-predictability as long as there are limits to arbitrage trading.

The main propositions of the thesis can further be stated into testable predictions, which will be the main ambition of this paper to analyse.

Prediction 1: The excess returns of an industry can be predicted by the lagged excess return of a commodity future that is economically linked to the relevant *industry, even when controlling for empirical market predictors.*

Prediction 2: Given a predictive power as outlined in Prediction 1, there are arbitrage opportunities in the form of anomalies in the market, which can yield abnormal returns.

To test the presented predictions, we first test the predictive power of lagged commodity futures to analyse *Prediction 1*. The methodology utilised is presented in Subsection 4.1. Furthermore, we present the methodological framework to analyse *Prediction 2* in Subsection 4.2.

3.1 Predictability Test

To test for the hypothesis of cross-asset predictability between commodity futures and economically linked industries, we utilise the Fama-MacBeth two-step methodology (Fama and MacBeth, 1973). Being widely recognised and commonly utilised in the academic literature, the approach is suited to analyse the linear relations between price changes in a financial instrument and proposed risk factors. In other words, the two-step methodology identifies if a risk factor is statistically significant in explaining changes in the underlying financial instrument. For example, for a test on a significant risk premium from commodity futures in equities, the conventional approach would be to analyse the relationship between the two in the cross-section of time, assuming no slow information diffusion and efficient markets. For this paper, however, slow information diffusion and inefficient markets are at the centre of the analysis. Our approach is, thus, to lag the price changes in commodity futures by different months to test if there is a linear relationship of statistical significance between past changes in commodity futures and present changes in the stock prices of industry portfolios. Furthermore, suppose such statistically significant risk premia for lagged commodity futures are identified. In that case, there is a strong indication of a gradual reaction to new information contained in the futures contracts of commodities that have a real effect on equity returns of industry portfolios.

Furthermore, and immensely relevant for our analysis, the Fama-MacBeth two-step procedure corrects the correlation of residuals in a system of equations. It thus eliminates the potential error in standard error coefficient estimates founded on cross-equation correlation. The procedure does, however, not correct for serial correlation in residuals. Serial correlation is thus corrected with Newey-West corrected standard errors (Newey and West, 1987) to achieve more robust test statistics. The precise methodology is presented below, starting from the first step of estimating a time series regression for each industry on each lagged commodity future alongside previously identified economic predictors.

$$r^e_{i,t} = c_{i,j,s} + \beta_{i,j,s} Com^e_{j,t-s} + \zeta_{i,j,s} Z_{t-1} + \epsilon_{i,j,s,t} \tag{1}$$

Where $r_{i,t}$ is the return in excess of the risk-free rate in period t for industry i, $Com_{j,t-s}$ is the excess returns of commodity future j, lagged by s months, and Z_{t-1} is a collection of previously identified indicators of economic returns, namely inflation, dividend yield, market volatility and market excess returns, all lagged by one month. Please refer to section 4.3 for a more detailed presentation of economic predictors. By including previously identified market predictors in the first step of the estimation, we aim to mitigate the potential commodity factor loading that is explanatory by other market predictors. $\beta_{i,j,s}$ is the factor loading on $Com^e_{j,t-s}$, while $\zeta_{i,j,s}$ is a system of coefficients for the previously identified market predictors(Z_{t-1}). The intercept of each regression, $c_{i,j,s}$ is included to allow for non-traded effects. The parameter is, however, not relevant for the further steps.

Note that each commodity future's excess return, lagged by s, is run as a separate system of equations. The reasoning for this is threefold. Firstly, we analyse data with a limited number of observations. Hence, running an augmented regression with multiple lags and multiple commodity futures will significantly increase the standard error estimates of our constructed coefficients and, consequently, the preciseness of our results. Secondly, as many commodity futures are contemporaneously correlated, an augmented regression can cause severe colinearity in the explanatory variables. Lastly and of great importance, not all commodity futures have available historical data back to the starting point of our analysis. Therefore, running each commodity future separately allows us to adapt each regression setup to the exact length of each commodity future and, thus, maximise the utilisation of our available sample set. On the other hand, we acknowledge that running each commodity future of a certain lag separately can present a bias in important omitted variables. Omitted variable bias is especially true for industry portfolios with intuitive economic links to more than one commodity. The bias is thus a definite bias to reflect on.

Utilising the estimated factor loadings $\hat{\beta}_{i,j,s}$ and $\hat{\zeta}_{i,j,s}$, the second step of the Fama-Macbeth methodology, which estimates risk premia for each risk factor through cross sectional regressions, is presented in Equation(2).

$$r_{i,t}^{e} = \lambda_{i,t,j,s}\hat{\beta}_{i,j,s} + \gamma_{i,t,j,s}\hat{\zeta}_{i,j} + \eta_{i,t,j,s} \tag{2}$$

Where $\lambda_{i,t,j,s}$ is a time series of risk premia for $Com_{j,t-s}^{e}$, while $\gamma_{i,t,j,s}$ is a matrix of risk premia for each market predictor in each time period ($\hat{\zeta}_{i,j}$) lagged with one month. $\eta_{i,t,j,s}$ is the residual of each cross sectional regression, and is interpreted as the pricing error of the regression.

The estimated risk premia, $\hat{\lambda}_{i,t,j,s}$, for commodity j with s lags on industry i is thus the variable of key interest for the analysis. Further deploying the methodology of Fama and MacBeth, we compute the expected value of the risk premia, and the standard error of the estimates in Equation(3) and Equation(4), respectively.

$$\hat{\lambda}_{i,j,s} = \frac{1}{T} \sum_{t=1}^{T} \lambda_{i,t,j,s} \tag{3}$$

$$SE(\hat{\lambda}_{i,j,s}) = \sqrt{\frac{1}{T^2} \sum_{t=1}^{T} (\lambda_{i,t,j,s} - \hat{\lambda}_{i,j,s})^2} \tag{4}$$

Where $\hat{\lambda}_{i,j,s}$ is the estimated risk premium of commodity future j lagged at s for industry i, and $SE(\hat{\lambda}_{i,j,s})$ is the standard error of the same estimated risk premium. Finally, the obtained estimates for the lagged commodity risk premium can be tested for statistical significance through the conventional ordinary least square framework and the t-test.

$$t - score_{i,j,s} = \frac{\hat{\lambda}_{i,j,s}}{SE(\hat{\lambda}_{i,j,s})} \tag{5}$$

As pointed out in recent years, a large number of the proposed anomalies in the financial market do not only fail to replicate in replicating studies but are also scrutinised through the wrong statistical lens due to multiple testing (Hou et al., 2020). The bias related to multiple testing occurs as a statistically significant value only represents a threshold for a given probability that the finding is correct (e.g. significant at a 5% level represents a $1 - 5\% = 95\%$ statistical probability that the result is correct), and running a large number of hypotheses will evidently produce false significant values. For the analysis of this paper, the bias of multiple testing is immensely relevant as we search for statistically significant cross-predictive returns from 27 commodity futures on 49 industries through a lagged span of one to five months. As such, we produce $27 * 49 * 5 = 6,615$ test statistics in total. At a 5% significance level, and assuming all commodities at all lags have no significant predictive power on industry returns, we will still expect to generate 331 significant findings. This vast number highlights the bias an analysis like ours can have towards multiple testing. Consequently, we incorporate a multi-testing framework with higher significance thresholds for test values to account for data mining, as presented by Harvey et al., 2016. The additional cutoffs are 2.78 and 3.36, reflecting an elevated level for 5%- and 1% significance levels, respectively.

3.2 Trading on Predictability

The second prediction of this thesis is that limits to arbitrage allow for the potential predictive power of commodity futures to be utilised in trading strategies that generate abnormal returns, even with current exploitation. To test this prediction, we construct strategies that allocate to the industries with the best-projected returns, according to the predictive tests presented in section 3.1. From the resulting $t - score$, we extract all estimated factor loadings from lagged commodity futures, $\hat{\beta}_{i,j,s}$, that are statistically significant. These factor loadings are then multiplied with the observed returns of the relevant commodity future at the relevant lag to generate an estimated effect each lagged commodity future will have on industry i in the next month. The exact formulation of this calculation is presented in Equation(6). We use each lagged commodity's estimated factor loading instead of the risk premia from the Fama-MacBeth two-step approach. The factor loading is used to calculate what the estimated impact of a change in the commodity price will have on each industry, commonly referred to as an economic impact. The same intuition from risk premia estimated is harder to interpret in the same intuitive fashion. However, we only incorporate the statistically significant relations identified by the two-step methodology, making the estimated risk premia a fundamental part of our constructed strategies.

$$\psi_{i,j,t+1,s} = \hat{\beta}_{i,j,s} * Com^{e}_{j,t-s+1} \tag{6}$$

Where $\psi_{i,j,t+1,s}$ is the estimated effect commodity j, lagged s months will have on industry i in the next months $(t+1)$. Note that the estimated factor loading is multiplied with the commodity future return of $t-s+1$, as the aim of the strategy is to predict future returns.

Further, we sum up all estimated predictive effects of a single commodity future, yielding a total estimated predictive price movement for every commodity future in every industry.

$$\sum \psi_{i,j,t+1} = \sum_{s=1}^{S} \psi_{i,j,t+1,s} \tag{7}$$

Where $\sum \psi_{i,j,t+1}$ is the total estimated predictive effect for all lagged excess returns of commodity future j on industry i. Calculating the full set of the predicted returns for every commodity future and industry further allows for a complete computation of the predicted excess returns of industry i, generated from all analysed commodity futures.

$$\Psi_{t+1,i} = \sum_{j=1}^{J} \psi_{i,j,t+1} \tag{8}$$

Where $\Psi_{t+1,i}$ is the complete predicted move in excess returns of industry i, generated from past excess returns of commodity futures. By utilising the estimated values of $\Psi_{t+1,i}$ in every time period t, we construct quantitative trading strategies that only allocate based on the predicted excess returns. Note that the approach presented only relies on historical information and is, thus, updated for each time period t to incorporate the newly observed information. Furthermore, some quantitative strategies utilise a long/short approach, effectively constructing net-zero investments. More details related to each strategy will be presented in section 5.2.

The outlined procedure for constructing quantitative strategies based on past information from commodity futures is finally tested for its potential to generate abnormal returns beyond established cross-sectional variables. To test this, and, thus, also *Prediction 2*, we run a time series regression for each constructed trading strategy on the exogenous variables highlighted in the Fama-French five-factor model (Fama and French, 1993). Namely these factors are *Mkt-rf, SMB, HML, RMW & CMA*. Please refer to section 4.4 for a more detailed description of the Fama-French factors. The factor model is presented in Equation(9).

$$r^e_{k,t} = \alpha_k + \beta_{k,M} Mkt^e_t + \beta_{k,S} SMB_t + \beta_{k,H} HML_t + \beta_{k,R} RMW_t + \beta_{k,C} CMA_t + \epsilon_{k,t} \tag{9}$$

Where $r^e_{k,t}$ is the excess return of the constructed quantitative strategy k in excess of the risk-free rate, and β_k is the factor loading of the strategy for each of the five included factors. α_k is the intercept of the regression and the measure of abnormal returns generated by the strategy. To test the statistical significance of all estimated coefficients, $\hat{\alpha}_k$ and $\hat{\beta}_k$, the $t-score$ is constructed in the same fashion as in Equation(5), with Newey-West robust standard errors for three months of lag. The analysis's critical estimate is the estimated model's intercept, α_k, and the corresponding $t-score$. If statistically significant, some strategy returns cannot be explained by the established risk factors of the model and instead represent abnormal returns through an unobserved source. In this analysis, the source of a statistically significant alpha would be the exploitation of the anomaly of cross-predictability from commodity futures to industry equities.

In addition to being a test for the efficiency of the market and the opportunity to benefit from the proposed anomaly of slow information diffusion from commodity futures to linked industries, the construction of trading strategies will be an interesting test to evaluate how a trading strategy rooted in the presented anomaly would actually perform in the market. Given the multi-testing bias of this thesis, as discussed in the latter stages of section 3.1, the test of trading strategies thus offers valuable insight into the real-life predictive nature of the vast set of data analysed.

4 Data

To carry out the analysis of this paper, we collect monthly historical data on industry returns from the US stock market, various commodity futures, risk factors and economic data from the beginning of 1970 until the end of 2021. The time frame is chosen to maximise the number of observations while not sacrificing variables due to insufficient data. We describe the exact data for each of the abovementioned categories of data in separate subsections below, alongside descriptive statistics of each data series.

4.1 US Industry Returns

Our data on industry returns from the US stock market is collected from the online database on Kenneth R. French's website. We collect the monthly total returns of 49 value-weighted industry portfolios defined by French. A complete table of all industries and the specification can be found in Appendix A.1. From 1970, the 49 collected industry return series have no missing values, which is why we use 1970 as the starting point for our analysis. Furthermore, utilising the French industry returns in the analysis allow our results to be more robust to biases that may arise when utilising single equities or self-constructed portfolios. Especially this applies to the measurement errors found in the inclusion of micro-cap equities, which can severely skew empirical findings (Hou et al., 2020). Utilising value-weighted portfolios mitigates this measurement error. However, note that firms with low market capitalisation are still included in the analysis and thus can contribute to some bias in industries with overall low market capitalisation. For this report's analysis, we aim to analyse economic links, and we thus include all industries to obtain the best differentiation in our analysis. Finally, all industry total return series are computed in excess of the risk-free rate, as collected from the website of French. Table 1 presents the summary statistics for all 49 US industry portfolio excess returns.

Table 1: Descriptive Statistics for All US Industries Analysed

Table 1: The table provides summary statistics for the monthly total returns in excess of the risk-free rate for 49 value-weighted industry portfolios in the US stock market in the time period between January 1970 and December 2021. The industry names are presented as their abbreviations. A table containing full names and a description can be found in the appendix. All values are reported in percentage points. Std is the standard deviation of the data series.

	Mean	Std	Min	Max
Aero	0.8344	6.9191	-35.99	32.50
Agric	0.6134	6.4112	-29.64	28.45
Autos	0.7489	7.6747	-36.50	49.56
Banks	0.6466	6.1471	-27.23	24.55
Beer	0.7597	5.2066	-20.19	25.51
BldMt	0.6955	6.3710	-31.89	34.40
nBooks	0.5442	6.0282	-25.27	30.73
Boxes	0.6347	5.7024	-28.82	20.19
BusSv	0.6406	5.6951	-28.24	24.80
Chems	0.6851	5.7680	-28.60	21.68
Chips	0.8377	7.5898	-32.62	26.85
Clths	0.7700	6.6701	-31.45	31.79
Cnstr	0.6188	7.3332	-32.14	23.61
Coal	0.6344	11.1324	-40.84	45.55
Drugs	0.7189	5.0074	-19.71	31.29
ElcEq	0.8205	6.4354	-32.80	22.87
FabPr	0.4889	7.5357	-32.62	30.37
Fin	0.7909	6.3192	-26.57	19.51
Food	0.7075	4.4821	-18.46	18.99
Fun	0.9690	7.7513	-32.48	39.30
Gold	0.5890	10.7601	-33.61	79.63
Guns	0.9305	6.4903	-30.47	31.88
Hardw	0.5963	7.2156	-33.88	24.94
Hlth	0.6447	8.0299	-39.61	35.89
Hshld	0.5346	4.6841	-22.25	18.22
Insur	0.7233	5.5423	-26.86	26.31
LabEq	0.7688	6.9346	-30.75	21.08
Mach	0.7030	6.4353	-31.91	23.02
Meals	0.7278	6.0958	-32.17	28.23
MedEq	0.7103	5.3206	-21.02	20.52
Mines	0.7222	7.6910	-34.83	26.95
Oil	0.6551	6.1607	-34.80	32.92
Other	0.1551	6.8018	-27.70	21.00
Paper	0.5585	5.5635	-27.08	24.19
PerSv	0.2827	6.6696	-28.85	24.06
RlEst	0.3139	7.6581	-37.59	66.01
Rtail	0.7635	5.5275	-29.72	26.51
Rubbr	0.7413	6.0384	-31.15	31.94
Ships	0.7016	7.4192	-32.87	29.15
Smoke	1.0052	6.2198	-25.32	32.38
Soda	0.7547	6.4623	-27.07	37.95
Softw	0.7269	10.2175	-36.44	73.11
Steel	0.4485	7.8291	-32.99	30.30
Telcm	0.5680	4.7597	-16.30	21.20
Toys	0.4716	7.3385	-35.01	26.42
Trans	0.6507	5.9170	-28.52	18.51
Txtls	0.6251	7.6224	-36.08	58.92
Util	0.5541	4.0885	-13.13	18.26
Whlsl	0.6117	5.5326	-29.28	17.47

4.2 Commodity Futures

To best analyse the impact of information contained in the prices of commodities, we utilise price data from generic 1st commodity futures, referring to a continuous contract constructed by the front-month (closest contract to expiration) futures. The argument for utilising the generic 1st contract compared to more distant maturities is that the front-month contract generally is the most liquid futures contract traded, allowing for the most accurate pricing of the underlying commodity. As futures are the conventional way of trading commodities, historical price data on commodity futures are more complete than spot prices. Furthermore, we only make use of one generic 1st futures contract per commodity. While many exchanges trade futures of the same commodity, this thesis does not aim to investigate pricing differences between these different exchanges, but rather the price changes of the underlying commodity. Thus, we select the contract with the highest historical trading volume, assuming that high liquidity allows for the most accurate pricing of the commodity. Some selection bias by the authors is present to obtain historical data that is both easily obtainable and of sufficient length.

From Bloomberg, we collect the monthly price changes of a broad spectrum of generic 1st futures contracts from various exchanges worldwide. The monthly price change is computed in US dollars for all futures to exclude effects caused by fluctuating exchange rates. Furthermore, only contracts with continuous trading every month from initiation until the end of 2021 are included. This criterion excludes contracts that have stopped trading or with such low liquidity that there are months without a single trade. We also impose a lower limit of 98 observations to ensure some robustness in statistical findings. For the commodity futures that pass the screening, we include all historical data from initiation on the exchange or back until January 1970, which is the first data point of our sample. Finally, as with the returns of the US industries, we subtract the risk-free rate from every month's price change to obtain the commodity futures return in excess of the risk-free rate. Again, we utilise the risk-free rate listed on the web page of Kenneth R. French. Table 2 presents summary statistics for every commodity futures contract included in the analysis. A complete summary of the included commodity futures, including the ticker and the relevant exchange of trade, can be found in Appendix A.2.

Table 2: Descriptive Statistics for All Commodity Futures Analysed

Table 2: The table provides summary statistics for the monthly excess returns of the most liquid generic 1st commodity futures of various commodities in the time period between January 1970 and December 2021. Each commodity name is followed by its abbreviation, which will be utilised in subsequent tables of the analysis. All values are reported in percentage points. Std is the standard deviation of the data series.

	Count	**Mean**	**Std**	**Min**	**Max**
Aluminium *(A)*	293	0.1707	5.5735	-16.28	16.94
Cattle *(Ca)*	625	0.0487	5.7677	-22.30	21.01
Cocoa *(Coc)*	625	0.2202	9.3396	-28.17	37.63
Coffee *(Cf)*	591	0.4325	10.8485	-31.23	58.86
Coking Coal *(CC)*	105	1.0537	11.7309	-27.92	37.24
Copper *(Cop)*	396	0.3343	7.3037	-36.55	35.06
Crude *(Cru)*	465	0.4806	10.6952	-54.36	88.37
Ethanol *(Eth)*	199	0.7859	10.9249	-34.66	50.92
Glass *(Gl)*	108	0.4866	8.8055	-21.86	30.80
Gold *(Go)*	563	0.2095	5.4468	-22.85	28.14
Hog *(H)*	428	0.4832	10.7371	-40.51	40.79
Iron *(I)*	98	0.4174	12.8503	-28.96	33.18
Lead *(L)*	293	0.6224	8.0756	-27.54	25.91
Lumber *(Lu)*	428	0.8391	11.5118	-45.32	58.41
Natural Gas *(NG)*	380	1.1379	15.1760	-42.16	62.60
Nickel *(N)*	293	0.6859	9.8803	-23.85	34.95
Palm Oil *(PO)*	321	0.4734	9.0964	-26.95	45.48
Platinum *(P)*	428	0.1515	6.3516	-32.01	33.37
Polyethelene *(Pe)*	173	0.1519	7.8276	-45.01	26.06
Polyvinyl Chloride *(PvC)*	151	0.4472	7.5853	-20.95	30.26
Pure Terephthalic Acid *(PTA)*	180	0.1038	8.5285	-31.54	39.80
Rice *(R)*	395	0.3253	8.4797	-29.62	47.80
Silver *(Si)*	563	0.3842	9.3487	-47.24	57.44
Soy *(So)*	625	0.2238	8.0808	-32.97	57.01
Sugar *(Su)*	625	0.6514	12.7296	-31.26	90.87
Tin *(T)*	293	0.7432	6.7942	-21.06	26.86
Wheat *(W)*	625	0.2453	8.3511	-26.39	42.32

As can be observed, a large number of the commodity futures do not have monthly data available back to the beginning of the sample period. This lack of data is due to the initiation of the futures contract later than 1970. Therefore, for all commodity futures with a later initiation date than 1970, all other data series in the given analysis are truncated to the same length.

4.3 Economic Predictors

In addition to lagged commodity futures returns, we utilise data on well-known economic predictors, as documented in prior empirical studies. These include lagged market returns, lagged inflation (Fama and Schwert, 1977), and the lagged market dividend yield (Campbell and Shiller, 1988). In addition, we construct a variable on lagged market volatility to ensure that commodity futures are not forecasting market volatility. All abovementioned variables are included in the analysis to ensure that any predictive nature of commodity futures does not proxy for other established market predictors. Lagged excess market returns are collected from the website of Kenneth R. French and calculated in excess of the risk-free rate retrieved from the same source. Data on inflation is retrieved from the Bureau of Labour Statistics through Refinitiv Workspace and is the monthly change in the complete consumer price index of the US, measured in percentage points. The lagged dividend yield of the US stock market is collected as monthly data points from the website of Robert Shiller through Refinitiv Workspace, and in the past year's dividend yield of the S&P500 measured in percentage points. Monthly market volatility is calculated as the standard deviation of the excess daily returns of the market portfolio in excess of the risk-free rate for the previous month. Again, the data is retrieved from the website and database of Kenneth R. French. The calculation procedure for market volatility is the same as that of French et al., 1987. Table 3 presents summary statistics for the economic predictors to be included in the analysis.

Table 3: Descriptive Statistics for All Economic Predictors Analysed

Table 3: The table provides summary statistics for the monthly data points on various documented market predictors in the time period between January 1970 and December 2021. All values are reported in percentage points and with a one-month lag. The market returns are in excess of the risk-free rate. Std is the standard deviation of the data series.

	Mean	**Std**	**Min**	**Max**
Lagged Market Returns	0.60	4.57	-23.24	16.10
Lagged Dividend Yield	2.84	1.22	1.11	6.24
Lagged Inflation	0.32	0.33	-1.77	1.81
Lagged Market Volatility	0.90	0.55	0.28	5.85

4.4 Factor Model

To test the performance of trading strategies rooted in the cross predictability between commodity futures and industry equity portfolios, we utilise the five-factor Fama-French cross-sectional regression, as described in section 3.2. Monthly time series data for the model is, again, collected from the online database of Kenneth R. French. Given the availability of the five risk factors of the five-factor model, we choose to utilise this framework instead of the more recently proposed and highly accredited q-factor model (Hou et al., 2015). The five-factor model thus allows for the analysis to be carried out without excessive data collection on market values and the other required data, which can be challenging to obtain for the total sample analysed in this paper. However, expanding the analysis with this additional step of data collection can be relevant in the case of statistically significant alpha generation through the five-factor model.

The factors collected from the website and utilised in the five-factor model are market excess returns, size, book-to-market, robustness, and aggressiveness. We refrain from presenting a detailed presentation of these risk factors in this paper, as a sufficient description is readily available through the website of Kenneth R. French and various other sources. However, we provide a brief note on each of the five risk factors to outline the economic relevance of each risk factor. The market excess return (Mkt^e) is the return on an overall value-weighted US equity portfolio in excess of the risk-free monthly rate (collected from the same source). The factor represents the risk premium of the equity market and is the foundation of the CAPM model (Sharpe, 1964, Lintner, 1965, Mossin, 1966). The risk factor for size (SMB) is the returns of a net-zero investment strategy that goes long equity portfolios with small market capitalisation and short portfolios with large market capitalisation. The underlying rationale for the size factor is that portfolios and equities of small size will be riskier and thus require a risk premium to investors. The factor for book-to-market (HML) is again a net-zero strategy that invests in portfolios of high book-to-market ratios and shorts the portfolios with the lowest values of the same ratio. As high ratios indicate a low valuation of the firm equity in comparison to the value of the balance sheet, the book-to-market factor is postulated to represent a proxy for the risk premium required for holding equities in financial distress. The three factors presented thus far are the risk factors with the heaviest empirical support and intuitive economic reasoning. They are also the factors utilised in the three-factor model developed by Fama and French (Fama and French, 1992). Their finished model expands on the fundamental three with two additional factors. Firstly, the factor on robustness (RMW) is constructed by going long and short portfolios of robust and weak operating profitability, respectively. Second and last, the factor of aggressiveness (CMA) is constructed as a strategy that is long portfolios with a conservative investment approach and short those with an aggressive investment approach.

5 Analysis

In this section, we present the results of our analysis and comment on the findings. First, the results related to *Prediction 1* will be discussed through the statistical results obtained by the two-step Fama-MacBeth methodology. Furthermore, the analysis on *Prediction 2* and the following results will be discussed in its own subsection, Subsection 5.2.

5.1 The Predictive Power of Commodity Futures

With 49 industry portfolios and 28 commodity futures at different lags, we simulate a substantial number of separate coefficients in the analysis of this paper. Reporting all variables would result in excessive and complex tables that complicate the delivery of what is meaningful. Our results will thus be presented in a distilled fashion, where only the risk premia of relevance to this analysis, namely the commodity futures, will be reported. Further, we do not report risk premia that display no significant predictive power and only present those relationships with statistical importance. However, to formalise the analysis, we present the full results from the two-step Fama-MacBeth methodology for one specific industry and commodity. The presented data in Table 4 is for the relation between the aluminium commodity future and the coal industry and display the estimated risk premia for up to three months of lag in the commodity future.

Table 4: Estimated Monthly Risk Premia from Sample Regression

Table 4: The table provides the estimated risk premia of economic predictors and the commodity future of aluminium at three different lags, represented through the three columns. The estimated risk premia is presented for all variables with corresponding t-values in parenthesis. * indicates at what significance level the risk premium is statistically significant. * = 10%, *2=5%, *3*1%. All other market predictors than the commodity remain unchanged throughout the three regressions at a lag of one month. Mkt^e_{t-1} is the market return in excess of the risk-free rate, DY_{t-1} is the monthly dividend yield lagged one month, INF_{t-1} is the monthly change in the complete consumer price index lagged one month, and $MVOL_{t-1}$ is the volatility of the market in the previous month. All coefficients are calculated on data in percentage points.

	t-1	*t-2*	*t-3*
Aluminium	0.3576	0.1647	0.1021
	*(2.3001)**2	*(1.4445)*	*(0.642)*
Mkt^e_{t-1}	0.235	0.3689	0.3818
	(0.8567)	*(1.3186)*	*(1.3106)*
DY_{t-1}	-2.7865	-2.7493	-2.768
	(1.0058)	*(1.0400)*	*(1.0543)*
INF_{t-1}	1.9784	2.4608	2.9178
	(0.6794)	*(0.8234)*	*(0.9521)*
$MVOL_{t-1}$	1.668	1.5695	1.456
	(0.9980)	*(0.9473)*	*(0.8763)*

We choose to highlight the relation between the coal industry and Aluminium futures in Table 4 as it offers crucial insight into the slow diffusion of information between a commodity and an industry, the key research question of interest for this paper. As both the coal industry and aluminium are highly relevant within the sector of industrial metals, there exists an intuitive economic link between the two, hinting to gradual information diffusion being a probable factor for statistically significant risk premia estimates in the analysis. As can be observed from Table 4, the one-month lagged excess returns of the aluminium futures have significant explanatory power in the excess returns of the coal industry. The risk premium is estimated to be 0.3576 and is significant at a 5% level (p-value of 0.0214). The statistically significant relation indicates that there is important information contained in the price movement of aluminium that is relevant in explaining the returns of the coal industry in the following month. The exact nature of what information contained in aluminium that is relevant for this specific industry is challenging to pinpoint, but that there exists causality in the information that reaches these assets at different points in time is not intuitively far-fetched. Moreover, no significant risk premium is detected for further lags of the aluminium futures contract, with two and three months displaying t-values far below any significant level. The result indicates that what information is relevant finishes its diffusion into the coal industry in the month directly following its incorporation into the aluminium future. The results thus indicate that aluminium futures contracts embody predictive power on the returns on the coal industry, with a one-month lag.

No significant risk premia are observed for all other included economic indicators, with t-values insignificant over the board. They, thus, do not portray explanatory predictive power for the coal industry. Moreover, the parameters for all economic indicators are more or less stable when tested in combination with the three different levels of lag in aluminium futures. Substantial fluctuations would indicate that the economic indicator, to some extent, contains the same information as the commodity. As we do not see this relation, and all economic indicators are insignificant, it is apparent that the information that makes the one-month lagged aluminium future significant is unique for this variable.

The insignificance and stability of the economic variables included in Table 4 also remain relatively constant throughout all estimated regressions, suggesting that the statistically significant information from the commodity futures is directly related to the specific commodity and not due to other economic factors. Furthermore, it is also a rationale for excluding the estimated premia for economic indicators in the further reported findings of our analysis and solely focusing on commodity futures and their corresponding estimated risk premia.

Table 5 presents the results from the Fama-MacBeth two-step methodology when running lagged commodity futures on all industry portfolios separately.

Given the sheer number of estimated risk premia, we do not report all estimated values but instead only focus on those of statistical significance below a level of 5%. Furthermore, as our analysis is inherently subject to the bias posed by multiple testing, we also refrain from reporting values that only find statistical support at the ten per cent level. The analysis is made on five different levels of lagged commodity futures, starting from month $t-1$ and testing for predictive nature in commodities five months back in time. Five lags are utilised to capture a wide span of the potential slow information diffusion and analyse how different commodities may diffuse differently to various industries. We also find it reasonable to stop at five lags, as we see a sharp drop-off in significant values at this level of lag.

Table 5: Statistically Significant Risk Premia per Industry

Table 5: The table provides the estimated risk premia of commodity futures of various lags on 49 industry portfolios from the US stock market, calculated through the two-step Fama-MacBeth methodology. Each industry is listed in a separate section, with the corresponding risk premia estimates in the column labelled $\hat{\lambda}$ and the t-value labelled $t - stat$. Each commodity future is labelled with its abbreviation and its lag $_{t-s}$. Every t-value is presented with an indication of its significance threshold. $*_2$ represents a 5% significance level, $*_3$ represents a 1% significance level, $*_4$ represents the adjusted 5% significance level of 2.78, and $*_5$ represents the adjusted 1% significance level of 3.36.

Aero$_t$	$\hat{\lambda}$	*t-stat*
H_{t-1}	0.48	*(2.86)*^{*4}
Pe_{t-1}	0.22	*(2.77)*^{*3}
PTA_{t-1}	0.15	*(2.42)*^{*2}
Lu_{t-2}	-0.66	*(1.98)*^{*2}
NG_{t-2}	0.45	*(2.19)*^{*2}
T_{t-2}	0.12	*(2.26)*^{*2}
A_{t-3}	0.16	*(2.87)*^{*4}
L_{t-3}	0.13	*(3.85)*^{*5}
So_{t-3}	0.68	*(2.16)*^{*2}
Su_{t-3}	0.53	*(2.41)*^{*2}
Pe_{t-4}	0.21	*(2.89)*^{*4}
PTA_{t-5}	0.15	*(2.91)*^{*4}

Agric$_t$	$\hat{\lambda}$	*t-stat*
PO_{t-1}	0.96	*(2.88)*^{*4}
Pe_{t-1}	0.16	*(2.38)*^{*2}
PvC_{t-1}	0.15	*(2.14)*^{*2}
So_{t-1}	0.84	*(2.57)*^{*2}
Gl_{t-2}	0.11	*(2.22)*^{*2}
Si_{t-2}	0.66	*(2.24)*^{*2}
W_{t-2}	0.74	*(2.42)*^{*2}
Coc_{t-3}	0.75	*(2.85)*^{*4}
Cf_{t-3}	0.56	*(2.64)*^{*3}
L_{t-3}	0.12	*(2.13)*^{*2}
So_{t-3}	0.97	*(2.62)*^{*3}
Su_{t-3}	0.41	*(1.97)*^{*2}
T_{t-3}	0.17	*(2.48)*^{*2}
Cru_{t-4}	-0.48	*(1.96)*^{*2}
Eth_{t-4}	-0.11	*(3.74)*^{*5}
L_{t-4}	0.11	*(2.19)*^{*2}
CC_{t-5}	0.75	*(2.16)*^{*2}

Autos$_t$	$\hat{\lambda}$	*t-stat*
Coc_{t-1}	-0.69	*(2.85)*^{*4}
Lu_{t-1}	0.81	*(2.42)*^{*2}
Pe_{t-1}	0.24	*(2.21)*^{*2}
A_{t-2}	0.21	*(2.45)*^{*2}
Cru_{t-2}	0.96	*(2.17)*^{*2}
L_{t-2}	0.11	*(2.31)*^{*2}
T_{t-2}	0.15	*(1.98)*^{*2}
Su_{t-3}	0.43	*(2.34)*^{*2}
Cru_{t-4}	-0.99	*(2.31)*^{*2}
Gl_{t-5}	0.23	*(2.36)*^{*2}
H_{t-5}	-0.93	*(2.77)*^{*3}

Banks$_t$	$\hat{\lambda}$	*t-stat*
PvC_{t-1}	0.14	*(2.17)*^{*2}
Coc_{t-2}	-0.68	*(2.41)*^{*2}
Coc_{t-3}	0.67	*(2.22)*^{*2}
Cru_{t-3}	0.54	*(2.21)*^{*2}
L_{t-3}	0.12	*(3.98)*^{*2}
N_{t-3}	0.15	*(2.72)*^{*3}
Pe_{t-3}	0.23	*(2.34)*^{*2}
PTA_{t-3}	0.16	*(1.97)*^{*2}
Su_{t-3}	0.52	*(2.74)*^{*3}

Beer$_t$	$\hat{\lambda}$	*t-stat*
Lu_{t-2}	-0.42	*(2.92)*^{*4}
N_{t-3}	0.79	*(2.83)*^{*4}
PTA_{t-3}	0.99	*(3.13)*^{*3}
Su_{t-3}	0.43	*(2.67)*^{*3}
I_{t-4}	0.56	*(1.99)*^{*2}

BldMt$_t$	$\hat{\lambda}$	*t-stat*
Lu_{t-1}	0.77	*(2.34)*^{*2}
CC_{t-2}	0.83	*(2.35)*^{*2}
L_{t-2}	0.92	*(2.17)*^{*2}
Coc_{t-3}	0.64	*(2.47)*^{*2}
Su_{t-3}	0.48	*(2.26)*^{*2}
CC_{t-4}	0.77	*(2.34)*^{*2}

Books$_t$	$\hat{\lambda}$	*t-stat*
Lu_{t-1}	0.64	*(2.45)*^{*2}
Pe_{t-1}	0.18	*(2.51)*^{*2}
Cru_{t-2}	0.71	*(2.26)*^{*2}
NG_{t-2}	0.35	*(2.22)*^{*2}
Coc_{t-3}	0.82	*(3.14)*^{*4}
N_{t-3}	0.82	*(2.29)*^{*2}
CC_{t-4}	0.73	*(2.17)*^{*2}
I_{t-4}	0.78	*(2.31)*^{*2}

Boxes$_t$	$\hat{\lambda}$	*t-stat*
H_{t-1}	0.61	*(2.48)*^{*2}
T_{t-1}	0.14	*(2.15)*^{*2}
Coc_{t-2}	-0.49	*(2.13)*^{*2}
I_{t-2}	0.79	*(2.39)*^{*2}
NG_{t-2}	0.37	*(1.99)*^{*2}
N_{t-2}	0.62	*(2.55)*^{*2}
A_{t-3}	0.97	*(2.16)*^{*2}
Coc_{t-3}	0.54	*(2.31)*^{*2}
Cf_{t-3}	0.47	*(2.14)*^{*2}
L_{t-3}	0.73	*(2.44)*^{*2}
H_{t-4}	-0.52	*(2.42)*^{*2}

BusSv$_t$	$\hat{\lambda}$	*t-stat*
Cop_{t-2}	0.75	*(2.69)*^{*3}
Cru_{t-2}	0.45	*(1.98)*^{*2}
Lu_{t-2}	-0.37	*(2.15)*^{*2}
T_{t-2}	0.13	*(2.72)*^{*3}
Coc_{t-3}	0.62	*(2.37)*^{*2}
N_{t-3}	0.67	*(2.32)*^{*2}
R_{t-3}	0.54	*(1.99)*^{*2}
So_{t-3}	0.82	*(2.74)*^{*2}
Su_{t-3}	0.51	*(2.72)*^{*3}
Ca_{t-5}	-0.96	*(2.18)*^{*2}

Chems$_t$	$\hat{\lambda}$	*t-stat*
Lu_{t-1}	0.75	*(3.55)*^{*5}
Pe_{t-1}	0.17	*(2.66)*^{*3}
T_{t-1}	0.13	*(1.97)*^{*2}
Coc_{t-2}	-0.47	*(2.33)*^{*2}
CC_{t-2}	0.67	*(2.28)*^{*2}
Cru_{t-2}	0.71	*(2.54)*^{*2}
L_{t-2}	0.11	*(2.54)*^{*2}
NG_{t-2}	0.45	*(2.44)*^{*2}
PTA_{t-2}	-0.13	*(2.43)*^{*2}
A_{t-3}	0.11	*(2.29)*^{*2}
Coc_{t-3}	0.59	*(2.58)*^{*3}
Go_{t-3}	0.88	*(2.38)*^{*2}
L_{t-3}	0.98	*(3.43)*^{*5}
N_{t-3}	0.84	*(2.61)*^{*3}
PTA_{t-3}	0.13	*(2.23)*^{*2}
R_{t-3}	0.81	*(2.98)*^{*4}
So_{t-3}	0.62	*(2.22)*^{*2}
Su_{t-3}	0.59	*(3.12)*^{*4}
T_{t-3}	0.13	*(2.17)*^{*2}
CC_{t-4}	0.87	*(2.13)*^{*2}
H_{t-4}	-0.49	*(2.14)*^{*2}
PO_{t-4}	0.75	*(1.97)*^{*2}
Coc_{t-5}	-0.64	*(2.29)*^{*2}
W_{t-5}	0.49	*(2.13)*^{*2}

Chips$_t$	$\hat{\lambda}$	*t-stat*
PTA_{t-1}	0.11	*(2.65)*^{*3}
T_{t-2}	0.17	*(2.78)*^{*4}
Gl_{t-4}	-0.15	*(2.46)*^{*2}

Clths$_t$	$\hat{\lambda}$	*t-stat*
Coc_{t-1}	-0.61	*(2.12)*^{*2}
Lu_{t-1}	0.54	*(2.16)*^{*2}
PO_{t-1}	0.92	*(2.79)*^{*4}
Pe_{t-1}	0.13	*(2.15)*^{*2}
L_{t-2}	0.98	*(2.98)*^{*4}
A_{t-3}	0.12	*(2.26)*^{*2}
Coc_{t-3}	0.66	*(2.77)*^{*3}
Cru_{t-3}	0.52	*(2.41)*^{*2}
Eth_{t-3}	0.68	*(2.24)*^{*2}
Go_{t-3}	0.92	*(1.96)*^{*2}
N_{t-3}	0.94	*(2.78)*^{*4}
I_{t-4}	0.83	*(2.14)*^{*2}
Ca_{t-5}	-0.11	*(2.18)*^{*2}
Lu_{t-5}	-0.43	*(2.29)*^{*2}

Cnstr$_t$	$\hat{\lambda}$	*t-stat*
Lu_{t-1}	0.56	*(2.13)*^{*2}
PO_{t-1}	0.88	*(2.71)*^{*3}
CC_{t-2}	0.99	*(2.63)*^{*3}
PvC_{t-2}	0.13	*(2.82)*^{*4}
Eth_{t-3}	0.97	*(2.61)*^{*3}
NG_{t-3}	0.52	*(2.73)*^{*3}
N_{t-3}	0.11	*(2.25)*^{*2}
R_{t-3}	0.14	*(2.87)*^{*4}
H_{t-5}	-0.66	*(2.15)*^{*2}

Coal$_t$	$\hat{\lambda}$	*t-stat*
A_{t-1}	0.35	*(2.31)*^{*2}
Lu_{t-1}	0.81	*(2.25)*^{*2}
Pe_{t-1}	0.27	*(2.76)*^{*3}
T_{t-1}	0.27	*(2.56)*^{*2}
Cop_{t-2}	0.24	*(2.21)*^{*2}
Gl_{t-2}	0.39	*(2.51)*^{*2}
L_{t-2}	0.17	*(2.16)*^{*2}
CC_{t-3}	-0.26	*(3.22)*^{*4}
NG_{t-3}	0.84	*(2.39)*^{*2}

Drugs$_t$	$\hat{\lambda}$	*t-stat*
Ca_{t-1}	-0.63	*(2.61)*^{*3}
Pe_{t-1}	0.13	*(2.22)*^{*2}
Cru_{t-2}	0.52	*(2.21)*^{*2}
Gl_{t-2}	0.91	*(1.99)*^{*2}
Su_{t-3}	0.48	*(2.73)*^{*3}
P_{t-5}	0.71	*(2.85)*^{*4}

ElcEq$_t$	$\hat{\lambda}$	*t-stat*
Lu_{t-1}	0.71	*(2.45)*^{*2}
PO_{t-1}	0.92	*(2.14)*^{*2}
Coc_{t-2}	-0.63	*(2.31)*^{*2}
CC_{t-2}	0.84	*(2.47)*^{*2}
Cru_{t-2}	0.71	*(2.12)*^{*2}
Lu_{t-2}	-0.41	*(1.99)*^{*2}
NG_{t-2}	0.54	*(2.57)*^{*2}
A_{t-3}	0.13	*(2.48)*^{*2}
I_{t-3}	-0.93	*(2.21)*^{*2}

			Su_{t-3}	0.67	$(2.38)^{*2}$				L_{t-3}	0.11	$(2.79)^{*4}$
			T_{t-3}	0.28	$(2.29)^{*2}$				N_{t-3}	0.92	$(2.11)^{*2}$
			L_{t-4}	0.24	$(2.39)^{*2}$				Su_{t-3}	0.48	$(2.55)^{*2}$
			N_{t-4}	0.18	$(2.14)^{*2}$						
			PvC_{t-4}	0.32	$(3.48)^{*5}$						
			Coc_{t-5}	-0.12	$(2.73)^{*3}$						
			PTA_{t-5}	0.21	$(2.32)^{*2}$						
			W_{t-5}	0.12	$(2.87)^{*4}$						

FabPr$_t$			**Fin**$_t$			**Food**$_t$			**Fun**$_t$		
	$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*
PO_{t-1}	0.11	$(2.48)^{*2}$	H_{t-1}	0.62	$(2.32)^{*2}$	H_{t-1}	0.36	$(2.38)^{*2}$	Lu_{t-1}	0.81	$(2.32)^{*2}$
Pe_{t-1}	0.17	$(2.24)^{*2}$	Pe_{t-1}	0.16	$(2.11)^{*2}$	T_{t-1}	0.15	$(2.45)^{*2}$	PO_{t-1}	0.12	$(1.99)^{*2}$
PTA_{t-1}	0.16	$(2.17)^{*2}$	PTA_{t-1}	0.15	$(2.63)^{*3}$	A_{t-2}	0.11	$(2.51)^{*2}$	Pe_{t-1}	0.26	$(2.72)^{*3}$
A_{t-2}	0.29	$(2.87)^{*4}$	Coc_{t-2}	-0.64	$(2.76)^{*3}$	Cop_{t-2}	0.57	$(2.13)^{*2}$	T_{t-1}	0.16	$(2.15)^{*2}$
Coc_{t-2}	-0.57	$(2.45)^{*2}$	Lu_{t-2}	-0.62	$(2.94)^{*4}$	Cru_{t-2}	0.63	$(2.57)^{*2}$	Cru_{t-2}	0.12	$(3.63)^{*2}$
Cru_{t-2}	0.13	$(3.42)^{*5}$	NG_{t-2}	0.42	$(2.66)^{*3}$	L_{t-2}	0.71	$(2.73)^{*3}$	L_{t-2}	0.18	$(2.12)^{*2}$
H_{t-2}	0.71	$(2.28)^{*2}$	T_{t-2}	0.19	$(2.14)^{*2}$	Coc_{t-3}	0.47	$(2.87)^{*4}$	NG_{t-2}	0.54	$(2.55)^{*2}$
L_{t-2}	0.11	$(2.32)^{*2}$	Coc_{t-3}	0.81	$(2.81)^{*4}$	N_{t-3}	0.43	$(2.11)^{*2}$	Su_{t-3}	0.65	$(2.52)^{*2}$
N_{t-2}	0.12	$(2.43)^{*2}$	L_{t-3}	0.11	$(2.38)^{*2}$	PTA_{t-3}	0.78	$(2.82)^{*4}$			
T_{t-2}	0.21	$(2.84)^{*4}$	Su_{t-3}	0.51	$(2.86)^{*4}$	Su_{t-3}	0.27	$(2.34)^{*2}$			
Cf_{t-3}	0.72	$(3.26)^{*4}$	Coc_{t-5}	-0.73	$(2.38)^{*2}$	Gl_{t-4}	-0.87	$(2.18)^{*2}$			
Cop_{t-3}	0.89	$(2.14)^{*2}$				P_{t-5}	0.89	$(2.16)^{*2}$			
L_{t-3}	0.11	$(2.82)^{*4}$									
Lu_{t-3}	0.77	$(2.54)^{*2}$									
N_{t-3}	0.91	$(2.11)^{*2}$									
So_{t-3}	0.84	$(2.37)^{*2}$									
CC_{t-4}	0.13	$(2.68)^{*3}$									

Go$_t$			**Guns**$_t$			**Hardw**$_t$			**Hlth**$_t$		
	$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*
Lu_{t-1}	0.18	$(2.75)^{*3}$	Lu_{t-3}	0.55	$(2.19)^{*2}$	PTA_{t-1}	0.16	$(2.72)^{*3}$	Pe_{t-1}	0.15	$(2.38)^{*2}$
PO_{t-1}	0.17	$(2.59)^{*3}$	R_{t-3}	0.67	$(2.97)^{*4}$	CC_{t-2}	0.79	$(2.47)^{*2}$	PTA_{t-1}	0.12	$(2.18)^{*2}$
H_{t-2}	0.14	$(3.31)^{*4}$	So_{t-3}	0.91	$(4.13)^{*5}$	Lu_{t-2}	-0.85	$(2.88)^{*4}$	Su_{t-1}	-0.69	$(1.96)^{*2}$
Gl_{t-3}	-0.28	$(2.12)^{*2}$	Su_{t-3}	0.55	$(2.85)^{*4}$	T_{t-2}	0.17	$(2.61)^{*3}$	Ca_{t-2}	0.12	$(2.79)^{*4}$
L_{t-4}	0.15	$(1.99)^{*2}$	Gl_{t-4}	-0.82	$(2.38)^{*2}$	Cf_{t-3}	0.78	$(2.67)^{*3}$	Cru_{t-2}	0.11	$(3.15)^{*4}$
Coc_{t-5}	-0.86	$(2.12)^{*2}$	Pe_{t-4}	0.23	$(2.57)^{*2}$	Lu_{t-3}	0.65	$(2.13)^{*2}$	Eth_{t-2}	0.59	$(2.42)^{*2}$
			Gl_{t-5}	-0.95	$(2.37)^{*2}$	PO_{t-3}	0.13	$(2.61)^{*3}$	H_{t-2}	0.53	$(2.12)^{*2}$
			I_{t-5}	-0.95	$(2.44)^{*2}$	Su_{t-3}	0.48	$(2.36)^{*2}$	Cop_{t-3}	0.79	$(2.16)^{*2}$
						Su_{t-4}	-0.45	$(2.31)^{*2}$	NG_{t-3}	0.44	$(2.15)^{*2}$
									N_{t-3}	0.64	$(2.35)^{*2}$
									R_{t-4}	0.76	$(2.42)^{*2}$
									H_{t-5}	-0.64	$(2.19)^{*2}$
									Lu_{t-5}	0.51	$(2.15)^{*2}$

Hshld$_t$			**Insur**$_t$			**LabEq**$_t$			**Mach**$_t$		
	$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*
T_{t-1}	0.81	$(2.18)^{*2}$	H_{t-1}	0.43	$(2.61)^{*3}$	A_{t-1}	0.13	$(1.99)^{*2}$	Lu_{t-1}	0.74	$(2.56)^{*2}$
Cru_{t-2}	0.52	$(2.57)^{*2}$	A_{t-2}	0.12	$(1.97)^{*2}$	Cru_{t-2}	0.86	$(2.69)^{*3}$	PTA_{t-1}	0.14	$(1.98)^{*2}$
PTA_{t-3}	0.11	$(2.91)^{*4}$	Cru_{t-2}	0.73	$(2.25)^{*2}$	Gl_{t-2}	0.85	$(2.98)^{*4}$	T_{t-1}	0.16	$(2.18)^{*2}$
Su_{t-3}	0.29	$(2.24)^{*2}$	L_{t-2}	0.81	$(2.16)^{*2}$	PvC_{t-2}	0.11	$(2.48)^{*2}$	CC_{t-2}	0.86	$(2.73)^{*3}$
Gl_{t-4}	-0.66	$(2.44)^{*2}$	Lu_{t-2}	-0.55	$(3.22)^{*4}$	T_{t-2}	0.14	$(2.69)^{*3}$	Cru_{t-2}	0.89	$(2.62)^{*3}$
			NG_{t-2}	0.59	$(3.67)^{*5}$	A_{t-3}	0.16	$(3.99)^{*5}$	A_{t-3}	0.18	$(3.44)^{*5}$
			Coc_{t-3}	0.46	$(2.24)^{*2}$	Cf_{t-3}	0.63	$(2.39)^{*2}$	Cf_{t-3}	0.65	$(3.22)^{*4}$
			Cop_{t-3}	0.77	$(2.52)^{*2}$	Cop_{t-3}	0.93	$(2.49)^{*2}$	L_{t-3}	0.19	$(2.56)^{*2}$
			L_{t-3}	0.71	$(1.98)^{*2}$	Lu_{t-3}	0.45	$(2.21)^{*2}$	Lu_{t-3}	0.64	$(2.26)^{*2}$
			N_{t-3}	0.95	$(2.81)^{*4}$	N_{t-3}	0.86	$(2.65)^{*3}$	N_{t-3}	0.11	$(2.59)^{*3}$
			PTA_{t-3}	0.14	$(2.18)^{*2}$	So_{t-3}	0.66	$(2.64)^{*3}$	PTA_{t-3}	0.13	$(2.53)^{*2}$
			Su_{t-3}	0.58	$(3.16)^{*4}$	Su_{t-3}	0.53	$(2.55)^{*2}$	R_{t-3}	0.99	$(2.72)^{*3}$
									So_{t-3}	0.93	$(2.52)^{*2}$
									CC_{t-4}	0.93	$(2.41)^{*2}$

Meals$_t$			**MedEq**$_t$			**Mines**$_t$			**Oil**$_t$		
	$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*
CC_{t-1}	0.55	$(2.92)^{*4}$	Pe_{t-1}	0.17	$(2.63)^{*3}$	Lu_{t-1}	0.96	$(3.32)^{*4}$	T_{t-1}	0.17	$(2.82)^{*4}$
Cru_{t-1}	-0.75	$(2.87)^{*4}$	PTA_{t-1}	0.12	$(2.44)^{*2}$	Pe_{t-1}	0.16	$(1.99)^{*2}$	Coc_{t-2}	-0.49	$(2.36)^{*2}$
PO_{t-1}	0.73	$(2.22)^{*2}$	A_{t-2}	0.11	$(2.51)^{*2}$	L_{t-2}	0.17	$(2.61)^{*3}$	Cop_{t-2}	0.16	$(2.98)^{*4}$
Pe_{t-1}	0.16	$(1.98)^{*2}$	Cru_{t-2}	0.97	$(5.48)^{*2}$	N_{t-2}	0.15	$(2.75)^{*3}$	L_{t-2}	0.15	$(3.72)^{*5}$
Cop_{t-2}	0.67	$(1.96)^{*2}$	Gl_{t-2}	0.12	$(2.26)^{*2}$	PTA_{t-2}	-0.18	$(2.38)^{*2}$	N_{t-2}	0.97	$(2.64)^{*3}$
Cru_{t-2}	0.45	$(2.16)^{*2}$	NG_{t-3}	0.34	$(2.17)^{*2}$	Go_{t-3}	0.15	$(2.38)^{*2}$	P_{t-2}	0.13	$(2.33)^{*2}$
L_{t-2}	0.88	$(3.28)^{*4}$	So_{t-3}	0.74	$(2.28)^{*2}$	N_{t-3}	0.11	$(2.12)^{*2}$	L_{t-4}	0.13	$(2.83)^{*4}$
A_{t-3}	0.91	$(1.96)^{*2}$	Su_{t-3}	0.42	$(2.24)^{*2}$	R_{t-3}	0.12	$(2.32)^{*2}$	N_{t-4}	0.13	$(1.96)^{*2}$
Coc_{t-3}	0.59	$(2.28)^{*2}$	NG_{t-5}	-0.38	$(2.91)^{*4}$	So_{t-3}	0.68	$(2.12)^{*2}$	Coc_{t-5}	-0.57	$(2.12)^{*2}$
Eth_{t-3}	0.58	$(2.28)^{*2}$	PO_{t-5}	0.68	$(3.26)^{*4}$	T_{t-3}	0.19	$(2.19)^{*2}$	Eth_{t-5}	0.64	$(2.18)^{*2}$
Lu_{t-3}	0.51	$(2.28)^{*2}$				Coc_{t-5}	-0.66	$(1.98)^{*2}$	So_{t-5}	0.65	$(2.00)^{*2}$
PTA_{t-3}	0.14	$(2.72)^{*3}$				Gl_{t-5}	0.22	$(3.26)^{*4}$	Su_{t-5}	0.33	$(2.61)^{*3}$
Su_{t-3}	0.51	$(3.17)^{*4}$									

Other$_t$			**Paper**$_t$			**PerSv**$_t$			**RlEst**$_t$		
	$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*
H_{t-1}	0.57	$(2.17)^{*2}$	Lu_{t-1}	0.54	$(2.51)^{*2}$	A_{t-2}	0.14	$(2.15)^{*2}$	PO_{t-1}	0.13	$(2.28)^{*2}$

Lu_{t-1}	0.61	$(2.65)^{*3}$	PO_{t-1}	0.61	$(2.42)^{*2}$	CC_{t-2}	0.79	$(2.84)^{*4}$	Pe_{t-1}	0.26	$(2.91)^{*4}$
PO_{t-1}	0.99	$(2.29)^{*2}$	Coc_{t-2}	-0.51	$(2.18)^{*2}$	Cru_{t-2}	0.77	$(2.91)^{*4}$	A_{t-2}	0.24	$(2.55)^{*2}$
Coc_{t-2}	-0.52	$(2.15)^{*2}$	L_{t-2}	0.16	$(2.47)^{*2}$	NG_{t-2}	0.49	$(3.63)^{*5}$	Coc_{t-2}	-0.59	$(2.22)^{*2}$
Lu_{t-2}	-0.55	$(2.21)^{*2}$	T_{t-2}	0.17	$(1.96)^{*2}$	T_{t-2}	0.11	$(2.21)^{*2}$			
NG_{t-2}	0.46	$(2.22)^{*2}$	A_{t-3}	0.11	$(3.45)^{*4}$	A_{t-3}	0.14	$(2.27)^{*2}$	NG_{t-2}	0.53	$(2.26)^{*2}$
T_{t-2}	0.14	$(2.39)^{*2}$	Coc_{t-3}	0.53	$(2.65)^{*3}$	Coc_{t-3}	0.57	$(2.97)^{*4}$	T_{t-2}	0.18	$(2.42)^{*2}$
Coc_{t-3}	0.63	$(2.13)^{*2}$	L_{t-3}	0.91	$(2.54)^{*2}$	Cru_{t-3}	0.46	$(2.16)^{*2}$	A_{t-3}	0.18	$(2.21)^{*2}$
Cru_{t-3}	0.67	$(2.93)^{*4}$	N_{t-3}	0.87	$(2.77)^{*3}$	L_{t-3}	0.15	$(2.74)^{*3}$	Coc_{t-3}	0.74	$(2.63)^{*3}$
N_{t-3}	0.82	$(2.14)^{*2}$	PTA_{t-3}	0.14	$(2.47)^{*2}$	NG_{t-3}	0.44	$(2.87)^{*4}$	Cru_{t-3}	0.59	$(2.27)^{*2}$
Pe_{t-3}	0.16	$(1.99)^{*2}$	So_{t-3}	0.79	$(2.28)^{*2}$	So_{t-3}	0.75	$(1.99)^{*2}$	Go_{t-3}	0.12	$(2.19)^{*2}$
PTA_{t-3}	0.16	$(2.24)^{*2}$	Su_{t-3}	0.46	$(2.91)^{*4}$	Su_{t-3}	0.49	$(2.28)^{*2}$	L_{t-3}	0.15	$(2.32)^{*2}$
Su_{t-3}	0.74	$(3.39)^{*5}$	PTA_{t-5}	0.88	$(2.32)^{*2}$	H_{t-4}	-0.58	$(1.96)^{*2}$	NG_{t-3}	0.56	$(2.79)^{*4}$
Ca_{t-5}	-0.15	$(2.31)^{*2}$				PTA_{t-5}	0.12	$(2.52)^{*2}$	N_{t-3}	0.11	$(3.93)^{*5}$
PO_{t-5}	0.91	$(2.36)^{*2}$							Su_{t-3}	0.71	$(2.89)^{*4}$
									T_{t-3}	0.17	$(2.43)^{*2}$
									Si_{t-4}	0.67	$(2.27)^{*2}$
									PTA_{t-5}	0.14	$(2.14)^{*2}$

Rtail$_t$			**Rubbr**$_t$			**Ships**$_t$			**Smoke**$_t$		
	$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*
Coc_{t-1}	-0.61	$(2.63)^{*3}$	Lu_{t-1}	0.65	$(1.97)^{*2}$	PO_{t-1}	0.18	$(2.19)^{*2}$	T_{t-1}	0.11	$(1.99)^{*2}$
Cru_{t-1}	-0.56	$(2.44)^{*2}$	PO_{t-1}	0.63	$(2.26)^{*2}$	Pe_{t-1}	0.21	$(2.42)^{*2}$	L_{t-4}	0.93	$(2.19)^{*2}$
So_{t-1}	-0.58	$(2.26)^{*2}$	A_{t-2}	0.17	$(2.35)^{*2}$	PTA_{t-1}	0.16	$(2.68)^{*3}$	Pe_{t-4}	0.11	$(2.65)^{*3}$
Cru_{t-2}	0.61	$(2.84)^{*4}$	Cru_{t-2}	0.76	$(2.24)^{*2}$	A_{t-3}	0.16	$(2.28)^{*2}$			
T_{t-2}	0.91	$(2.41)^{*2}$	L_{t-2}	0.16	$(2.18)^{*2}$	Coc_{t-3}	0.81	$(2.54)^{*2}$			
Coc_{t-3}	0.51	$(2.46)^{*2}$	PvC_{t-2}	0.11	$(3.89)^{*5}$	L_{t-3}	0.14	$(3.62)^{*5}$			
Su_{t-3}	0.59	$(2.43)^{*2}$	T_{t-2}	0.16	$(2.62)^{*3}$	Lu_{t-3}	0.77	$(2.58)^{*3}$			
Cru_{t-4}	-0.54	$(2.13)^{*2}$	A_{t-3}	0.12	$(2.69)^{*3}$	PTA_{t-3}	0.18	$(2.32)^{*2}$			
Gl_{t-4}	-0.12	$(2.55)^{*2}$	Coc_{t-3}	0.54	$(2.25)^{*2}$	R_{t-3}	0.92	$(2.15)^{*2}$			
Go_{t-4}	-0.84	$(2.25)^{*2}$	Cf_{t-3}	0.54	$(2.67)^{*3}$	So_{t-3}	0.86	$(2.63)^{*3}$			
CC_{t-5}	0.64	$(2.15)^{*2}$	Cop_{t-3}	0.86	$(1.99)^{*2}$	T_{t-3}	0.16	$(2.25)^{*2}$			
			Eth_{t-3}	0.65	$(2.93)^{*4}$	Pe_{t-4}	0.24	$(2.48)^{*2}$			
			Lu_{t-3}	0.43	$(2.25)^{*2}$	Cop_{t-5}	0.78	$(2.12)^{*2}$			
			PO_{t-3}	0.18	$(2.27)^{*2}$	PTA_{t-5}	0.14	$(2.16)^{*2}$			
			PTA_{t-3}	0.16	$(2.14)^{*2}$						
			Su_{t-3}	0.43	$(2.54)^{*2}$						

Soda$_t$			**Softw**$_t$			**Steel**$_t$			**Telcm**$_t$		
	$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*
A_{t-1}	0.15	$(2.12)^{*2}$	PTA_{t-1}	0.13	$(2.11)^{*2}$	A_{t-1}	0.25	$(2.86)^{*4}$	Coc_{t-1}	-0.47	$(2.38)^{*2}$
Coc_{t-3}	0.57	$(2.29)^{*2}$	So_{t-1}	-0.11	$(2.18)^{*2}$	Lu_{t-1}	0.94	$(2.26)^{*2}$	Coc_{t-2}	-0.39	$(2.14)^{*2}$
Cf_{t-3}	0.65	$(2.39)^{*2}$	Cop_{t-2}	0.92	$(2.33)^{*2}$	Pe_{t-1}	0.28	$(2.93)^{*4}$	Cru_{t-2}	0.81	$(3.56)^{*5}$
Eth_{t-3}	0.81	$(2.45)^{*2}$	Lu_{t-2}	-0.46	$(2.86)^{*4}$	PTA_{t-1}	0.25	$(2.38)^{*2}$	Lu_{t-2}	-0.51	$(3.23)^{*4}$
PTA_{t-3}	0.16	$(3.34)^{*4}$	T_{t-2}	0.15	$(2.71)^{*4}$	A_{t-2}	0.18	$(1.96)^{*2}$	Su_{t-2}	-0.31	$(2.88)^{*4}$
T_{t-3}	0.11	$(2.35)^{*2}$	Ca_{t-3}	0.14	$(2.12)^{*2}$	Coc_{t-2}	-0.78	$(2.52)^{*2}$	T_{t-2}	0.92	$(2.45)^{*2}$
T_{t-4}	-0.11	$(2.53)^{*2}$	Go_{t-3}	0.12	$(2.33)^{*2}$	N_{t-2}	0.12	$(2.45)^{*2}$	A_{t-3}	0.92	$(2.12)^{*2}$
Pe_{t-5}	-0.85	$(2.19)^{*2}$	PO_{t-3}	0.13	$(2.57)^{*2}$	P_{t-2}	0.21	$(2.65)^{*3}$	L_{t-3}	0.54	$(2.15)^{*2}$
			Su_{t-3}	0.15	$(3.57)^{*5}$	T_{t-2}	0.23	$(2.76)^{*3}$	Su_{t-3}	0.44	$(3.59)^{*5}$
			Gl_{t-4}	-0.16	$(3.55)^{*5}$	A_{t-3}	0.17	$(2.13)^{*2}$	Cru_{t-4}	-0.37	$(2.14)^{*2}$
						Cf_{t-3}	0.65	$(2.58)^{*3}$	I_{t-5}	0.58	$(1.97)^{*2}$
						L_{t-3}	0.19	$(3.54)^{*5}$			
						N_{t-3}	0.11	$(2.18)^{*2}$			
						R_{t-3}	0.11	$(2.41)^{*2}$			
						Su_{t-3}	0.65	$(2.85)^{*4}$			
						T_{t-3}	0.19	$(2.18)^{*2}$			
						CC_{t-4}	0.17	$(2.14)^{*2}$			
						Pe_{t-4}	0.21	$(1.96)^{*2}$			
						Gl_{t-5}	0.21	$(2.45)^{*2}$			
						W_{t-5}	0.87	$(2.53)^{*2}$			

Toys$_t$			**Trans**$_t$			**Txtls**$_t$			**Util**$_t$		
	$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*		$\hat{\lambda}$	*t-stat*
Gl_{t-1}	0.17	$(2.21)^{*2}$	Lu_{t-1}	0.56	$(2.36)^{*2}$	Pe_{t-1}	0.21	$(2.63)^{*3}$	Coc_{t-1}	-0.47	$(2.58)^{*3}$
H_{t-1}	0.86	$(2.87)^{*4}$	Pe_{t-1}	0.16	$(2.92)^{*4}$	Coc_{t-2}	-0.54	$(2.32)^{*2}$	Cru_{t-2}	0.41	$(2.11)^{*2}$
I_{t-1}	0.19	$(2.84)^{*4}$	CC_{t-2}	0.74	$(2.12)^{*2}$	L_{t-2}	0.14	$(2.31)^{*2}$	Su_{t-2}	-0.23	$(2.58)^{*3}$
Pe_{t-1}	0.18	$(2.44)^{*2}$	T_{t-2}	0.11	$(2.24)^{*2}$	NG_{t-2}	0.57	$(2.47)^{*2}$	L_{t-3}	0.56	$(2.62)^{*3}$
A_{t-2}	0.21	$(2.43)^{*2}$	A_{t-3}	0.16	$(2.99)^{*4}$	P_{t-2}	0.16	$(2.35)^{*2}$	P_{t-3}	0.71	$(2.72)^{*3}$
Cop_{t-2}	0.88	$(1.96)^{*2}$	L_{t-3}	0.12	$(3.81)^{*5}$	T_{t-2}	0.17	$(1.99)^{*2}$	PTA_{t-3}	0.74	$(2.31)^{*2}$
Cru_{t-2}	0.78	$(2.11)^{*2}$	N_{t-3}	0.85	$(2.46)^{*2}$	Coc_{t-3}	0.62	$(2.46)^{*2}$	Su_{t-3}	0.25	$(2.95)^{*4}$
L_{t-3}	0.92	$(2.12)^{*2}$	PTA_{t-3}	0.16	$(2.72)^{*3}$	Eth_{t-3}	0.14	$(2.25)^{*2}$	L_{t-4}	0.71	$(2.29)^{*2}$
N_{t-3}	0.15	$(2.56)^{*2}$	Su_{t-3}	0.57	$(3.47)^{*5}$	Su_{t-3}	0.63	$(2.91)^{*4}$	Eth_{t-5}	0.45	$(2.51)^{*2}$
PO_{t-3}	0.16	$(2.57)^{*2}$	T_{t-3}	0.15	$(2.39)^{*2}$	I_{t-4}	0.13	$(2.68)^{*3}$	P_{t-5}	0.73	$(2.37)^{*2}$
Su_{t-3}	0.55	$(2.66)^{*3}$	Pe_{t-4}	0.19	$(3.19)^{*4}$						
I_{t-4}	0.14	$(2.15)^{*2}$	R_{t-5}	-0.72	$(2.95)^{*4}$						

Whlsl$_t$		
	$\hat{\lambda}$	*t-stat*
Pe_{t-1}	0.15	$(2.62)^{*3}$
A_{t-2}	0.12	$(2.23)^{*2}$
CC_{t-2}	0.57	$(2.23)^{*2}$
Cru_{t-2}	0.65	$(2.79)^{*4}$
T_{t-2}	0.98	$(2.14)^{*2}$

A_{t-3}	0.12	$(2.86)^{*4}$			
Cf_{t-3}	0.45	$(2.44)^{*2}$			
Go_{t-3}	0.73	$(2.16)^{*2}$			
L_{t-3}	0.73	$(2.42)^{*2}$			
N_{t-3}	0.69	$(2.69)^{*3}$			
PTA_{t-3}	0.13	$(2.59)^{*3}$			
So_{t-3}	0.81	$(2.59)^{*3}$			
Su_{t-3}	0.52	$(3.15)^{*4}$			
T_{t-3}	0.96	$(2.12)^{*2}$			

As can be observed from the magnitude of Table 5, a substantial number of commodity futures are estimated to carry predictive characteristics on US industry returns. In total, 560 estimated risk premia are identified at a statistically significant level of 5%, and every analysed industry is estimated to have a relation to at least three lagged commodity returns. Though there is a great difference in the number of significant predictors among the industries, the clear overall result of the analysis indicates that there is valuable information in commodity futures that are not efficiently priced into the US equity market. In other words, the overall results of the Fama-MacBeth two-step methodology suggest that commodity futures, to a varying extent, can predict future movements in industry returns.

With the magnitude of identified predictors, every commodity and every industry has the potential to be analysed in-depth for a more comprehensive understanding. Having analysed such a large number of relations, we focus on a broader scope in our further analysis and leave more specific cases for future research on the topic. We also heavily weight observations with more substantial t-values in our further analysis of the results. This emphasis on strengthened statistical thresholds is again due to the prevalent multi-testing bias in our calculations. From this point onward, we thus characterise statistical significance as being above the modified threshold for 5% significance of 2.78 for the test statistic. The high cutoff is not to say that all estimated risk premia below this cutoff should be deemed irrelevant. Instead, it functions as a tool to highlight the more statistically robust findings of the analysis. Consequently, the following discussions only reflect on risk premia of modified statistical significance below the 5% level.

A key observation from the estimated risk premia in Table 5 is that none of the 560 significant estimates are above one percentage point. The effects of all lagged commodity premia are, therefore, of a relatively small scale, on average. To some extent, this is expected, given that the commodities are lagged and thus contain information that has been public for at least one month. Observing substantial risk premia would thus indicate substantial inefficiencies in the market. However, given their small magnitude, it is therefore also somewhat surprising that the number of significant coefficients is as considerable as the data suggest. Standard errors of the estimates are thus also limited, yielding significant t-statistics.

The main research question of this thesis is to analyse the potential effects of slow information diffusion and the predictive effects it may have. For the information to be relevant, there must also be an economic link between the analysed commodity futures and the industry they are found to predict. One must admit that this feat is overwhelming, with 560 observed predictive relations. It is, for example, not easy to directly connect the information contained in three-month lagged sugar futures (Su_{t-3}) to the returns of the industry portfolio containing insurance companies (Insur_t). However, the risk premia of this predictive relation are firmly statistically significant, with a t-value of 3.16, reaching the threshold for the 5% significance level, even with our adjusted cutoff requirement. This obscure relation is not our results' outlier but the majority. While it is highly plausible that a fair share of these variables contain unique information that obscurely and indirectly affects the identified industries, we find it more reasonable that the commodity futures serve as a proxy for broader market information and incorporate this into prices more effectively than equity markets. A prominent example of such a relation is inflation, which is previously documented to have predictive features on the equity market (Fama and Schwert, 1977). While one-month lagged inflation is accounted for in the analysis of this paper, by including it in the initial step of the Fama-MacBeth two-step methodology, we do not account for further lags. To some extent, commodity futures can, thus, proxy further lags of inflation. Moreover, it can intuitively be argued that many commodities also lead inflation by experiencing lasting price changes at an earlier stage than the overall consumer price index of the US market. In some instances, commodity futures can, thus, be a better proxy for inflation than the changes in the consumer price index itself. A prime example of this potential phenomenon can be observed in our analysis's case of sugar futures (Su). Considering the elevated threshold for significance of 2.78 for the test statistic at a 5% level, sugar is estimated to be the commodity with the most statistically significant risk premia, totalling 16 separate premia across the 49 industries. As previously mentioned, many of these industries do not have any reasonable direct connection to the price changes of sugar. What sugar does have, however, is a significant relation to many goods contained in the basket of goods utilised for the consumer price index. Moreover, and in support of inflation being a significant player in the estimated premia for sugar, we observe that a large number of the statistically significant predictive power of sugar comes with a substantial lag, usually of three months. Assuming a general delay from an increase in the commodity price to the incorporation of the greater cost into the prices of finished products, this lag matches well with the narrative of sugar leading the consumer price index, and thus the returns of much of the equity market. We highlight sugar here, as it is immensely prevalent in our results. The same economic reasoning can, however, also be argued for many of the other commodity futures analysed, such as cocoa (Coc), lumber (Lu), and rice (R), with five, seven, and four statistically significant risk premia estimates, respectively (at the 5% level with the elevated cutoff of 2.78 for the test statistic). Therefore, while obscure at first glance, we argue that there might very well be an economic link connecting these commodity futures to the industries, supporting the hypothesis of predictive returns through slow information diffusion.

Building on the intuition of various commodities proxying as indicators for fundamentals that affect future returns of industries, it is also interesting to observe that precious metals (namely gold (Go), platinum (P) and silver (Si)) have close to no predictive power on industry returns. Gold and silver are actively traded commodity futures that are closely related to current and future expected inflation. However, this relationship is primarily driven by inflation as a leading indicator, and thus it is not surprising to observe that the commodities lead few industry returns. Furthermore, and reflecting on the rationale presented in the previous paragraph, not many goods in the consumer price index are heavily reliant on precious metals. Therefore, the lack of observed significant risk premia for precious metals supports the postulated relationship between commodity futures and future inflation as one of the key explanatory factors in explaining the observed cross-predictability.

More direct economic links are also observed in the results presented in Table 5. These direct relations are arguably most evident in the industry portfolio of transportation ($Trans$). Six separate lagged commodity futures are estimated to contain predictive features on the transportation industry returns, more than any other portfolio in our analysis. While this industry specification contains many industries that cannot be said to have a direct relation to the commodity futures, it also has constituent industries like railroads, freight and freight forwarding, all tightly connected to commodities. For these sectors, it is clear that price changes in commodities will affect the profits and costs. The fact that we do observe cross predictive power in lagged commodities such as polyethelene (Pe)(a common form of plastic), aluminium (A), and lead (L) is thus arguably an indication of a lag in information in the link between commodity futures and equities.

Other than the transportation industry, however, one does not observe a large number of relations that can be intuitively connected to increases/decreases in profits for an industry further down a supply chain (considering the elevated threshold for statistical significance). In some sense, the results indicate that the market is quite efficient in pricing the information directly relevant to each industry. For example, and perhaps not surprising for anyone, we find no evidence for the predictive power in the oil futures contract of the WTI on the US oil industry. Therefore, it is clear that investors, at least to some extent, do not limit their attention to only the equity market. The same observation is also done in various other industries. For instance, no industrial metals predict the mining industry and lumber possess no predictive power in the paper industry. Thus, to a large extent, our results indicate that the information that slowly diffuses from commodities to equities is not directly related to the changes in profits or costs but rather to other, and more complex, economic links between the two asset classes. As previously discussed, inflation intuitively seems to be one such complex relation. Further convoluted indirect implications on profits and costs are another.

The estimated risk premia can also provide insight into the importance of easily accessible information. As is thoroughly investigated in the equity markets, the number of analysts covering a company or industry reduces the misplacing observed (Brennan et al., 1993). The same reasoning should hold for commodities as well, where the relevance of a commodity and its coverage will result in greater attention from the market as a whole and thus a reduced existence of predictive relations between the respective commodity and the market. The undisputed commodity that should reflect this behavioural trait is oil, represented by the WTI futures contract in our analysis. Moreover, industrial metals like iron ore, aluminium and copper also represent heavily monitored commodities due to their impact on the broad economy. Interestingly, it is exactly these commodities that are documented to lead the market in previous literature. Oil is identified to possess a predictive lead relation on the SP500 index, in addition to various single US stocks (Narayan and Sharma, 2011; Wang et al., 2019), and aluminium and copper are identified to lead stock markets (Jacobsen et al., 2019). In our analysis, we do observe this leading ability through significant risk premia for all of these three commodities, but to the extent that somewhat reflects the attention investors pay to them. For oil and aluminium, we observe a substantial number of risk premia in various industries. However, the predictive power for both commodities is mostly only significant at a lag of three months or more. This delayed reaction is strange behaviour to observe for commodity futures that are so heavily monitored. The fact that so few risk premia are identified at one and two lags suggests that the market efficiently prices the changes in the commodity prices. On the other hand, with the significant premia identified at further lags, there is clearly some delayed movement in equities, reflecting an initial underreaction to the changes. One can postulate that two different variations of information are accountable for this effect. Firstly, information directly connected to industries is priced efficiently and does not diffuse into the equities at a lag. Second, commodity price changes also reflect obscure information with a more complex and long-lasting effect on industries. Consequently, investors fail to price in the information when it first becomes available and only incorporates it when the information becomes more directly relatable to the given industry.

Lastly, it is informative to connect our analysis presented in Table 5 to the existing literature on cross predictability. As presented in section 2 of this paper, empirical research has indicated that various industries do lead the overall market (Torous et al., 2007), and that equity returns of suppliers often lead those of consumers (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010). Both findings support the theory of slow information diffusion and the effect of this phenomenon on asset pricing. Like the abovementioned papers, our analysis also identifies cross predictability that seemingly stems from slow information diffusion throughout the asset classes and expands the observed universe of cross predictability research to the intercept between the two asset classes of commodities and equities. Furthermore, the utilisation of five lags in the commodity future returns allows for valuable insight into how the information reaches the various affected industries at different points in time. Therefore, in many ways, we look further back towards the initiation of some of the new information that might be the factors causing the cross predictability between industries and the market. For example, when we observe that six separate commodity futures at different lags predict the future returns of the transportation industry, and Menzly and Ozbas, 2010 identify that the transportation industry leads the market, are the commodities the initial information carriers? Or when suppliers are observed to lead consumers, are some commodities at different lags an explanatory factor in the equation? A large number of intriguing research questions can be raised from our findings in relation to existing literature, research questions we hope will be further investigated in the future. What seems clear from both our research and that of previous authors on cross-predictability is that the financial markets are littered with inefficiencies in violation of the efficient market hypothesis.

5.2 Trading on Commodity Cross-Predictability

With an immense body of identified risk premia in equity industries stemming from lagged commodity futures, there seem to be ample opportunities to trade on the predictive power of commodity futures in the equity market. Therefore, testing the potential paper profits (before transaction costs) of simple trading strategies built on the obtained information is an interesting analysis to make. Is there actual money to be made in the market by utilising the estimated risk premia of lagged commodity futures? An analysis of the potential trading returns also brings another dimension to our analysis. Namely, if the information on estimated risk premia from lagged commodities is an observation that can only be made in hindsight or if the information can be continuously utilised through the sample period.

One must consider that the methodology utilised in this paper is not groundbreaking. An assumption that investors already utilise this information is, thus, not far-fetched. The question to ask then is if there should be any possibility of making money in the actual market. As outlined in the opening stages of Section 3, findings of cross predictability that yields abnormal returns would indicate one of two things. Either there are no investors in the market currently utilising the information contained in older commodity futures, or there are limits to arbitrage, as proposed by Shleifer and Vishny, 1997. Naturally, the first alternative is improbable, and any abnormal returns identified should be considered to support the theory of limits to arbitrage.

To test the performance of trading strategies that exploit the identified risk premia of lagged commodities, we utilise the methodology outlined in Subsection 3.2 to obtain what we define as an "estimated predicted move". To keep with the trend of strengthened statistical robustness, we only choose to estimate risk premia for commodities with more than 100 months of sample data and only evaluate risk premia estimates above the elevated threshold of 5% significance (test statistic above 2.78). Given the total risk premia estimated and the observed lagged moves in the respective commodity futures (see Subsection 3.2 for further details), we predict which industries will be the best and worst performers next month. The exploiting strategies utilise these predictions to take both long and short positions. The trading strategies are run in the time frame between the year 2000 until the end of 2021. The start date is chosen to allow a decent number of observations to be available for estimation at the beginning of the test period. To reiterate a vital specification presented in Subsection 3.2, our strategies re-estimate the estimated risk premia and factor loadings for every month that passes, utilising all available information back to 1970. Therefore, the risk premia estimates applied in the trading strategies do not rely on future information and only rely on available information at every point in time. The trading strategy has also been allowed to be back-tested with predictive coefficients estimated on the entire sample (1970-2021). As the risk premia results in Table 5 indicate, such strategies naturally yield immense returns compared to the market. However, with future information utilised, these strategies yield no empirical results with impact, and we refrain from reporting it in this paper.

Table 6 presents the descriptive statistics of the tested strategies, including both net-zero strategies and long-only alternatives. A figure of the cumulative returns from each strategy is also available in the appendix of this paper. We refrain from reporting it in the text, as it offers little insight outside of what the table on descriptive statistics does.

Table 6: Descriptive Statistics for Trading Strategies

Table 6: The table provides descriptive statistics for the excess returns of the proposed trading strategies and the market portfolio, all in excess of the risk-free rate. Mean is the monthly mean excess return of the portfolio, std is the standard deviation, and min/max reflects the minimum and maximum observations in the time period. The Sharpe ratio, trivially the risk-adjusted return of each strategy, is defined as $\frac{r^e}{\sigma(r^e)} * \sqrt{12}$, where r^e is the excess return and $\sigma(r^e)$ is the standard deviation of the excess returns. The Sharpe ratio is scaled to reflect the annual risk-adjusted return. $Corr(Mkt^e, x)$ is the correlation between the excess return of the market portfolio and each of the included strategies. Mkt^e is the value-weighted market portfolio, $Long/Short^e_x$ is a strategy that goes long (short) the top (bottom) x estimated performing industries based on the calculated factor loadings in each period. $Long^e_x$ is a strategy that goes along the top x estimated performing industries based on the calculated factor loadings in each period. All reported statistics on mean, standard deviation, and min and max are presented in percentage points.

	Mkt^e	$Long/Short^e_5$	$Long/Short^e_{10}$	$Long^e_5$	$Long^e_{10}$
count	263	263	263	263	263
mean	0.6261	-0.1329	0.0641	0.6974	0.8426
std	4.5096	3.3533	2.4241	5.2437	5.0651
min	-17.23	-10.37	-7.855	-24.064	-21.561
max	13.65	9.512	7.31	16.144	15.327
Skewness	-0.5441	-0.1027	-0.0413	-0.4113	-0.4886
Kurtosis	1.1069	0.6670	0.5039	2.0094	2.0436
Sharpe Ratio	0.4809	-0.1373	0.0916	0.4607	0.5763
$Corr(Mkt^e, x)$	1.000	-0.0948	-0.0804	0.8500	0.9035

As can be observed from Table 6, we run the predictive trading strategies as both a net-zero strategy, meaning equal amounts long and short, and as a long-only strategy. The mean excess returns of these strategies vary to a great extent, with the net-zero approaches delivering results that only slightly differ from zero on a monthly basis. For example, for the $Long/Short^e_{10}$- strategy, the mean excess monthly return is 0.0641%, more than 50 basis points below the performance of the market portfolio in the same period. Even worse are the results generated from the less diversified $Long/Short^e_5$, which yields a monthly excess return of -0.1329% in the test period. Given these results in mean, there seems to be slim evidence of a net-zero strategy actually performing in the market. On the other hand, the mean excess returns generated from the long-only strategies yield more promising results, generating a mean of 0.6974% and 0.8426% for the $Long^e_5$ and $Long^e_{10}$, respectively. Compared to the mean market return of 0.6261%, both strategies thus deliver somewhat more promising results throughout the tested time frame.

The mean excess return of a portfolio or trading strategy should not be viewed in isolation from the risks taken. The strategy risk is, consequently, an essential factor in the evaluation of performance. Building on the relation between the mean excess return and the risk taken, Table 6 also presents the risk-adjusted return of each portfolio, formally named the Sharpe Ratio. For the long-short strategies, we can observe that the risks taken are reduced compared to that of the market portfolio. With both long and short positions in the market, macroeconomic shocks that equally (or close to) affect all industries are, thus, somewhat hedged. The reduced volatility of these net-zero strategies is therefore not surprising. Still, compared to the returns and risk taken in holding the market portfolio, the reduced risk of the hypothetical net-zero strategies constructed on the predictive power of commodity futures does not generate a risk-return trade-off that is anywhere close to optional. The results are more appealing for the long-only strategy, with only slightly higher volatility than the market portfolio. Again, a slight increase in volatility for these strategies is expected, as the mean-variance diversification is less optimal than that of the market, and idiosyncratic risks can generate more significant impacts. Interestingly, both long strategies deliver an enhanced risk-adjusted return compared to the market portfolio, with Sharpe Ratios of 0.4607 and 0.5763 for the $Long^e_5$ and $Long^e_{10}$, respectively. The outperformance of the market, which in general is considered close to the optimal trade-off of risk and return, is suggestive that the industry selection based on commodities may generate some attractive returns in the actual market.

An interesting statistical observation can also be made in the skewness of the constructed strategies. Even with higher volatility, both long strategies offer a less negatively skewed (left-skewed) distribution in returns than the market. The reduced skewness reflects a more normal return distribution and less of a dragged-out tail of negative returns. On the other hand, the kurtosis of the investment long-only strategies is quite a bit higher than that of the market, reflecting that the tails of the distributions are more substantial than that of the market. To indicate that the long-only strategies are less prone to outlier observations is therefore not a conclusion that can be drawn. For the net-zero strategies, both the skew and the kurtosis are lower than that of the market. Again, reflecting the nature of a long-short strategy and its hedging features, this observation is not of great surprise. The correlations can further imply the intrinsic hedging abilities of the net-zero strategies to the market, which are close to zero. On the other hand, the long-only strategies naturally correlate substantially to the market as a whole.

The projected performance of the trading strategies based on the predictive nature of commodity futures is somewhat appealing and suggestive of an opportunity to generate abnormal returns by trading equity industries purely based on past information contained in commodity futures. However, the descriptive statistics reported in Table 6 do not attempt to explain the fundamental origin of the returns. It is this differentiation the Fama-French five-factor methodology aims to make. Efficient capital markets propose that risk factors should generate higher expected returns. The returns of the basic trading strategies constructed should thus be corrected for well-established risk factors in the cross-section of time before one can suggest that the abnormal returns of the strategy can be attributed to the predictive nature of commodity futures and the consequential slow information diffusion across the markets. Table 7 represents the results from the estimation of the Fama-French five-factor model, utilising the regression specification outlined in Equation(9).

Table 7: Regression Results from the Fama-French 5-Factor model

Table 7: The table provides the estimated coefficients from the Fama-French five-factor model, with corresponding absolute test statistics in parenthesis. Every t-value is constructed with Newey-West robust standard errors for three months of lag and with an indication of its significance threshold. $*$ represents a 10% significance level, $*_2$ represents a 5% significance level, $*_3$ represents the adjusted 5% significance level of 2.78, and $*_5$ represents the adjusted 1% significance level of 3.36. $Long/Short^e_x$ is a strategy that goes long (short) the top (bottom) x estimated performing industries based on the calculated factor loadings in each period. $Long^e_x$ is a strategy that goes long the top x estimated performing industries based on the calculated factor loadings in each period. $\hat{\alpha}$ is the estimated intercept of the regression model, $\hat{\beta}_{Mkt^e}$ is the estimated factor loading on the market portfolio in excess of the risk free rate, and $\hat{\beta}_{SMB}$, $\hat{\beta}_{HML}$, $\hat{\beta}_{RMW}$ and $\hat{\beta}_{CMA}$ are the estimated factor loading for SMB, HML, RMW and CMA, respectively (see Subsection 4.4 for a detailed explanation). The Appraisal Ratio is the abnormal returns of each strategy, adjusted for the residual risk, defined as $\frac{\hat{\alpha}}{\sigma(\epsilon_t)}$, where $\sigma(\epsilon_t)$ is the standard deviation of the residual in each regression. The regression model is calculated on values in percentage points.

	$Long/Short^e_5$	$Long/Short^e_{10}$	$Long^e_5$	$Long^e_{10}$
$\hat{\alpha}$	-0.1055	0.1706	-0.1739	-0.0134
	(0.493)	*(0.980)*	*(0.912)*	*(0.094)*
$\hat{\beta}_{Mkt^e}$	-0.0405	-0.0585	1.0257	1.0357
	(0.701)	*(1.430)*	*(19.126)*$*_5$	*(24.730)*$*_5$
$\hat{\beta}_{SMB}$	-0.0705	-0.0513	0.2006	0.2284
	(0.704)	*(0.786)*	*(2.336)*$*_2$	*(4.118)*^{*5}
$\hat{\beta}_{HML}$	-0.0080	0.0215	0.1067	0.1623
	(0.094)	*(0.290)*	*(1.347)*	*(2.524)*$*_2$
$\hat{\beta}_{RMW}$	0.0528	-0.1025	0.2470	0.2288
	(0.501)	*(1.228)*	*(3.157)*$*_4$	*(3.340)*$*_4$
$\hat{\beta}_{CMA}$	0.0137	-0.0042	0.1390	0.0644
	(0.089)	*(0.037)*	*(1.168)*	*(0.696)*
Appraisal Ratio	-0.0314	0.0703	-0.0676	-0.0071
R^2	0.017	0.015	0.764	0.862

From the results of the Fama-French regression presented in Table 7, one can observe that many of the established risk factors of the model have explanatory power over the generated returns of the constructed strategies. Firstly, a great loading on the market portfolio is evident for the long-only strategies, with 1.03 and 1.04 in market beta for the $Long^e_5$ and $Long^e_{10}$, respectively. The estimated factor loading is also statistically significant beyond any doubt for both. The fact that the market risk premium is a significant factor in explaining the excess returns of the long-only strategy carries intuitive logic from basic economic intuition. The well-diversified market portfolio will represent the general risk premium for holding equities (Sharpe, 1964, Lintner, 1965, Mossin, 1966). Holding a pure equity portfolio, as the constructed long-only strategies are, should, thus, earn the risk premium of equities. It is consequently not surprising to see that the net-zero strategies do not have a significant market beta, given that the short position contributes to eliminating the market risk premium of the long position. Following the same intuition of a general equity risk premium, it is also confirming to see that the estimated market beta of both strategies is close to one.

For the factor loading on the risk premium generated from owning smaller firms, namely the factor of SMB, it is again observable that the long-only strategies have some dependence. With statistical significance at a 5% level, the $Long_5^e$-strategy has a coefficient of 0.20 and the $Long_{10}^e$ one of 0.23. Keeping the composition of the SMB-factor in mind, the industry selection constructed from the predictive nature of lagged commodity futures, thus, does seem to load on smaller industries and the risks and rewards associated with it. On the other hand, the net-zero strategies show no significant factor loading on the risks of smaller firms. Moreover, with the statistically significant relation found in the long-only strategies, it is again evident that the short position of the net-zero strategy is zeroing out the effect. In other words, there seems to be a similar loading on SMB for both the long and short positions chosen by the model.

For the HML factor, only the factor loading of the $Long_{10}^e$-strategy is statistically significant at a 5% level. The coefficient of 0.16 identifies that the strategy does have some of the same behaviour in returns as a net-zero strategy purely loading on the risk of low book values. Therefore, the economic consensus of a risk premium for holding firms in financial distress seems to be reflected in the most diversified long-only strategy. For the remaining three strategies, the estimated coefficients are not at a statistically significant level. The same argument for equal loading in both the long and short positions of the $Long/Short_{10}^e$-strategy can again be made for this factor.

While commonly not as well accepted as Fama and French's three previously discussed factors, our constructed long-only strategies are estimated to have a statistically explanatory loading on the RMW factor. The estimated coefficients, which are statistically significant for both presented long-only strategies at a 5% level, are 0.2470 and 0.2288 for the $Long_5^e$ and $Long_{10}^e$, respectively. Both factor coefficients are approximately the same size as those estimated for the factor loading on SMB, suggesting that our constructed portfolios load approximately equal on the risk premiums earned by smaller firms and of firms with more robust profitability. The economic intuition for the factor of RWW is somewhat obscure compared to that of the first three of the model, as the prior is assumed to proxy for risk factors and a corresponding premium demanded by investors. A portfolio of robust profitability minus one of weak profitability does not seemingly represent a risk. Nonetheless, the factor is often found to have statistical explanatory power on returns, as is the case for our long-only strategies. The general long-only strategies based on the predictive power of commodity futures, thus, seem to load significantly on the cross-sectional factor of RMW. We again see no significant loading for the net-zero strategies, backing the rationale of an intrinsic hedge.

For the last factor of the Fama-French five-factor model, namely CMA, there is no estimated factor loading on any statistically significant level. The strategies, thus, do not seem to be explained by the investment policies of firms.

More interesting are the returns of the constructed strategies that are not explained by any factors, specifically the alpha (α). Firstly, it is clear that none of the strategies constructed on the predictive power of commodity futures generates any abnormal returns after correcting for the established risk factors of the Fama-French five-factor model. The statistical insignificance is observable through the low test statistics. Given the insignificance of the alpha estimates, one should be careful interpreting them too much. However, one noteworthy feature should be discussed. Correcting for all risk factors and our strategies' loading on them, both long-only strategies are estimated to have an intercept of negative value. The economic intuition is consequently that the strategies underperform compared to the identified factor loadings. Given the promising mean returns and Sharpe Ratios of the strategies presented in Table 6, the result of the five-factor model severely shifts the projected performance. The long-only strategies constructed based on cross predictability from commodity futures consequently do not generate any abnormal returns and rather underperform given the risk factors they load on. On the other hand, the $Long/Short^{e}_{10}$-strategy, which generates negative mean excess returns throughout the test period, is estimated to have a positive alpha (though statistically insignificant). With all estimated coefficients below any statistically significant level, no conclusions can be drawn about the actual performance of this strategy. It is, however, interesting to observe this change in sign from mean returns to alpha, suggesting that the $Long/Short^{e}_{10}$-strategy would generate positive returns with a hedge against all five risk factors.

Taking a step back, key conclusions can be drawn from the estimates of the Fama-French five-factor model in relation to the cross-predictive nature of various commodity futures identified in Subsection 5.1. First, from the factor regressions, it is clear that the predictive properties of commodities in individual industries do not generate a profit in the true marketplace but rather load on established risk factors in the cross-section of time. This conclusion is not a result that directly discredits the finding of statistically significant predictive power in commodity futures but rather a result that brings further insight into the estimates presented in Subsection 5.1.

Firstly, market participants may adapt to eliminate the predictive nature over time and adapt quicker than our model identifies statistically significant relationships. As previously stated, it is naive to believe that our simple analysis and trading strategy has not been previously analysed and adopted by quantitative investors. Thus one would expect any predictive power to be quickly eliminated unless there exist limits to arbitrage trading (Shleifer and Vishny, 1997). Therefore, the five-factor regression model delivers a firm answer to the second prediction of this paper. No, there are no abnormal returns obtainable based on the predictive nature of commodity futures, suggesting that arbitrage trading eliminates all anomalies over time. Consequently, we do not identify any limits to arbitrage trading.

Second, the identified statistically significant risk premia in Subsection 5.1 may, to a large extent, be explained by a smaller number of observations with significant explanatory impact. In such a case, the proposed generic trading strategy will fall short and expect much greater predictive power than what is the case for most periods. A more dissected analysis is then necessary for an investor to construct a more robust trading strategy. An example of dissection will be a distinction between economic expansions and recessions, which are previously identified to affect the leading nature of some industrial commodity futures (Jacobsen et al., 2019). We have refrained from such dissection in this paper due to the large number of analysed relationships. Nonetheless, it is an intriguing distinction for future research, which could yield conflicting results on how effectively the market corrects the identified anomalies.

Lastly, one can argue that returns generated from the cross predictability of commodity futures coincide with the risk factors of the Fama-French model and consequently are, to a larger extent, present in the generation of returns. However, given the large body of research on the five risk factors in the five-factor model and the economic intuition behind them, such argumentation is not something we consider to be reasonable in explaining the returns of our predictive strategies.

6 Conclusion

We find that price changes in a large number of commodity futures can predict movements in equity returns of US industry portfolios. The findings suggest that information contained in commodity prices only gradually diffuses across the financial market and is only priced by the relevant equities with a lag. Our results align with previous research in the field of cross-predictability and slow information diffusion, and we extend the findings to a broad cross-asset relationship between commodities and equities. Interestingly, we find little evidence of predictive power from commodities to industries with a strong economic link, suggesting that investors with specialisation within an industry efficiently incorporate information about the most relevant commodities. Instead, most of our statistically significant commodity predictors have a more obscure relationship with the respective industries they lead, indicating a complex relation that investors only incorporate into prices with a lag. Considering our research alongside previous empirical research on the nature of cross-predictability and lead-lag relations in financial markets, we highlight the interconnected nature these lead-lag relationships might have in mapping information diffusion across financial markets and the implications it has for efficient markets.

Furthermore, we find that the identified predictive power of commodity futures cannot be utilised to generate abnormal returns in the financial market. Instead, we find that any excess return generated from our simple exploitative trading strategies is attributed to factor loading on the factors of the Fama-French five-factor model. With no statistically significant alpha found for either long-only or net-zero strategies, we postulate that the predictive nature of commodities is gradually incorporated by arbitrage traders and eliminated from the market over time. No limits to arbitrage are therefore identified in our analysis. Alternatively, such substantial differences exist in the predictive nature of commodity futures over time that a more comprehensive dissection is needed to accurately trade on the anomalies.

Our identified cross-predictive nature between a large number of commodities and equities raises intriguing questions to be analysed in future research. Firstly, the analysis conducted in this paper does not make any distinctions in macroeconomic conditions when estimating the predictive power of commodity futures on specific industries. For example, seeing how a differentiation between recessions and expansions will affect the estimates can bring further economic insight into the predictive nature of commodity futures. With macroeconomic distinctions, both the predictive test and a trading strategy performance can bring new and valuable insight. Furthermore, with a leading relationship from a large number of commodities to equities, and previous literature identifying the same lead in option volumes on equities (Pan and Poteshman, 2006), there still is limited research on information diffusion to and from fixed income securities. While more complex to collect data from, cross predictability in fixed income can carry new intuition that further deepens the understanding of the topic. Finally, as our analysis has been on a large number of industries and commodities, no extensive in-depth analysis has been conducted on the identified predictive nature of select commodities and specific industries. We thus hope our analysis can serve as a stepping stone for further, more qualitative research on each commodity's impact on individual industries.

A APPENDIX

A.1 Additional Tables

Table A1: Table of Industry Name and Specifications

Table A1: The table present the full industry names for the abbreviations utilised in the paper. In addition further specification about the constituents of each industry is provided, combined with the corresponding SIC code. The reported classification is identical to that found on the website of Kenneth R. French.

1	**Agric**	**Agriculture**
		0100-0199 Agricultural production - crops
		0200-0299 Agricultural production - livestock
		0700-0799 Agricultural services
		0910-0919 Commercial fishing
		2048-2048 Prepared feeds for animals
2	**Food**	**Food Products**
		2000-2009 Food and kindred products
		2010-2019 Meat products
		2020-2029 Dairy products
		2030-2039 Canned & preserved fruits & vegetables
		2040-2046 Flour and other grain mill products
		2050-2059 Bakery products
		2060-2063 Sugar and confectionery products
		2070-2079 Fats and oils
		2090-2092 Misc food preparations and kindred products
		2095-2095 Roasted coffee
		2098-2099 Misc food preparations
3	**Soda**	**Candy & Soda**
		2064-2068 Candy and other confectionery
		2086-2086 Bottled-canned soft drinks
		2087-2087 Flavoring syrup
		2096-2096 Potato chips
		2097-2097 Manufactured ice
4	**Beer**	**Beer & Liqueur**
		2080-2080 Beverages
		2082-2082 Malt beverages
		2083-2083 Malt
		2084-2084 Wine
		2085-2085 Distilled and blended liquors
5	**Smoke**	**Tobacco Products**
		2100-2199 Tobacco products
6	**Toys**	**Recreation**
		0920-0999 Fishing, hunting & trapping
		3650-3651 Household audio visual equipment
		3652-3652 Phonograph records
		3732-3732 Boat building and repairing
		3930-3931 Musical instruments
		3940-3949 Toys
7	**Fun**	**Entertainment**
		7800-7829 Services - motion picture production and distribution
		7830-7833 Services - motion picture theaters
		7840-7841 Services - video rental
		7900-7900 Services - amusement and recreation
		7910-7911 Services - dance studios
		7920-7929 Services - bands, entertainers
		7930-7933 Services - bowling centers
		7940-7949 Services - professional sports
		7980-7980 Amusement and recreation services (?)
		7990-7999 Services - Misc entertainment
8	**Books**	**Printing and Publishing**
		2700-2709 Printing publishing and allied
		2710-2719 Newspapers: publishing-printing
		2720-2729 Periodicals: publishing-printing
		2730-2739 Books: publishing-printing
		2740-2749 Misc publishing
		2770-2771 Greeting card
		2780-2789 Bookbinding
		2790-2799 Service industries for the print trade
9	**Hshld**	**Consumer Goods**
		2047-2047 Dog and cat food
		2391-2392 Curtains, home furnishings

		2510-2519 Household furniture 2590-2599 Misc furniture and fixtures 2840-2843 Soap & other detergents 2844-2844 Perfumes, cosmetics and other toilet preparations 3160-3161 Luggage 3170-3171 Handbags and purses 3172-3172 Personal leather goods, except handbags and purses 3190-3199 Leather goods 3229-3229 Pressed and blown glass 3260-3260 Pottery and related products 3262-3263 China and earthenware table articles 3269-3269 Pottery products 3230-3231 Glass products 3630-3639 Household appliances 3750-3751 Motorcycles, bicycles and parts (Harley & Huffy) 3800-3800 Misc instruments, photo goods & watches 3860-3861 Photographic equipment (Kodak etc, but also Xerox) 3870-3873 Watches, clocks and parts 3910-3911 Jewelry, precious metals 3914-3914 Silverware 3915-3915 Jewelers' findings and materials 3960-3962 Costume jewelry and novelties 3991-3991 Brooms and brushes 3995-3995 Burial caskets
10	**Clths**	**Apparel** 2300-2390 Apparel and other finished products 3020-3021 Rubber and plastics footwear 3100-3111 Leather tanning and finishing 3130-3131 Boot & shoe cut stock & findings 3140-3149 Footwear, except rubber 3150-3151 Leather gloves and mittens 3963-3965 Fasteners, buttons, needles, pins
11	**Hlth**	**Healthcare** 8000-8099 Services - health
12	**MedEq**	**Medical Equipment** 3693-3693 X-ray, electromedical app 3840-3849 Surgical, medical, and dental instruments and supplies 3850-3851 Ophthalmic goods
13	**Drugs**	**Pharmaceutical Products** 2830-2830 Drugs 2831-2831 Biological products 2833-2833 Medicinal chemicals 2834-2834 Pharmaceutical preparations 2835-2835 In vitro, in vivo diagnostic substances 2836-2836 Biological products, except diagnostic substances
14	**Chems**	**Chemicals** 2800-2809 Chemicals and allied products 2810-2819 Industrial inorganic chemicals 2820-2829 Plastic material & synthetic resin/rubber 2850-2859 Paints 2860-2869 Industrial organic chemicals 2870-2879 Agriculture chemicals 2890-2899 Misc chemical products
15	**Rubbr**	**Rubber and Plastic Products** 3031-3031 Reclaimed rubber 3041-3041 Rubber & plastic hose & belting 3050-3053 Gaskets, hoses, etc 3060-3069 Fabricated rubber products 3070-3079 Misc rubber products (?) 3080-3089 Misc plastic products 3090-3099 Misc rubber and plastic products (?)
16	**Txtls**	**Textiles** 2200-2269 Textile mill products 2270-2279 Floor covering mills 2280-2284 Yarn and thread mills 2290-2295 Misc textile goods 2297-2297 Non-woven fabrics 2298-2298 Cordage and twine 2299-2299 Misc textile products 2393-2395 Textile bags, canvas products 2397-2399 Misc textile products
17	**BldMt**	**Construction Materials** 0800-0899 Forestry 2400-2439 Lumber and wood products 2450-2459 Wood buildings & mobile homes

		2490-2499 Misc wood products 2660-2661 Building paper and board mills 2950-2952 Paving & roofing materials 3200-3200 Stone, clay, glass, concrete, etc 3210-3211 Flat glass 3240-3241 Cement, hydraulic 3250-3259 Structural clay products 3261-3261 Vitreous china plumbing fixtures 3264-3264 Porcelain electrical supplies 3270-3275 Concrete, gypsum & plaster products 3280-3281 Cut stone and stone products 3290-3293 Abrasive and asbestos products 3295-3299 Misc nonmetallic mineral products 3420-3429 Cutlery, hand tools and general hardware 3430-3433 Heating equipment & plumbing fixtures 3440-3441 Fabricated structural metal products 3442-3442 Metal doors, frames 3446-3446 Architectural or ornamental metal work 3448-3448 Prefabricated metal buildings and components 3449-3449 Misc structural metal work 3450-3451 Screw machine products 3452-3452 Bolts, nuts, screws, rivets and washers 3490-3499 Misc fabricated metal products 3996-3996 Hard surface floor coverings
18	**Cnstr**	**Construction** 1500-1511 Build construction - general contractors 1520-1529 General building contractors - residential 1530-1539 Operative builders 1540-1549 General building contractors - non-residential 1600-1699 Heavy construction - not building contractors 1700-1799 Construction - special contractors
19	**Steel**	**Steel Works etc** 3300-3300 Primary metal industries 3310-3317 Blast furnaces & steel works 3320-3325 Iron & steel foundries 3330-3339 Primary smelting & refining of nonferrous metals 3340-3341 Secondary smelting & refining of nonferrous metals 3350-3357 Rolling, drawing & extruding of nonferrous metals 3360-3369 Nonferrous foundries and casting 3370-3379 Steel works etc 3390-3399 Misc primary metal products
20	**FabPr**	**Fabricated Products** 3400-3400 Fabricated metal, except machinery and trans eq 3443-3443 Fabricated plate work 3444-3444 Sheet metal work 3460-3469 Metal forgings and stampings 3470-3479 Coating, engraving and allied services
21	**Mach**	**Machinery** 3510-3519 Engines & turbines 3520-3529 Farm and garden machinery and equipment 3530-3530 Construction, mining & material handling machinery & equipment 3531-3531 Construction machinery & equipment 3532-3532 Mining machinery & equipment, except oil field 3533-3533 Oil & gas field machinery & equipment 3534-3534 Elevators & moving stairways 3535-3535 Conveyors & conveying equipment 3536-3536 Cranes, hoists and monorail systems 3538-3538 Machinery 3540-3549 Metalworking machinery & equipment 3550-3559 Special industry machinery 3560-3569 General industrial machinery & equipment 3580-3580 Refrigeration & service industry machinery 3581-3581 Automatic vending machines 3582-3582 Commercial laundry and dry cleaning machines 3585-3585 Air conditioning, warm air heating and refrigeration equipment 3586-3586 Measuring and dispensing pumps 3589-3589 Service industry machinery 3590-3599 Misc industrial and commercial equipment and machinery
22	**ElcEq**	**Electrical Equipment** 3600-3600 Electronic & other electrical equipment 3610-3613 Electric transmission and distribution equipment 3620-3621 Electrical industrial apparatus 3623-3629 Electrical industrial apparatus 3640-3644 Electric lighting & wiring equipment 3645-3645 Residential electric lighting fixtures 3646-3646 Commercial, industrial and institutional electric lighting fixtures 3648-3649 Misc lighting equipment

		3660-3660 Communications equipment 3690-3690 Misc electrical machinery and equipment 3691-3692 Storage batteries 3699-3699 Misc electrical machinery, equipment and supplies
23	**Autos**	**Automobiles and Trucks** 2296-2296 Tire cord and fabric 2396-2396 Automotive trimmings, apparel findings & related products 3010-3011 Tires and inner tubes 3537-3537 Industrial trucks, tractors, trailers & stackers 3647-3647 Vehicular lighting equipment 3694-3694 Electrical equipment for internal combustion engines 3700-3700 Transportation equipment 3710-3710 Motor vehicles and motor vehicle equipment 3711-3711 Motor vehicles & passenger car bodies 3713-3713 Truck & bus bodies 3714-3714 Motor vehicle parts & accessories 3715-3715 Truck trailers 3716-3716 Motor homes 3792-3792 Travel trailers and campers 3790-3791 Misc transportation equipment 3799-3799 Misc transportation equipment
24	**Aero**	**Aircraft** 3720-3720 Aircraft & parts 3721-3721 Aircraft 3723-3724 Aircraft engines & engine parts 3725-3725 Aircraft parts 3728-3729 Misc aircraft parts & auxiliary equipment
25	**Ships**	**Shipbuilding, Railroad Equipment** 3730-3731 Ship building and repairing 3740-3743 Railroad Equipment
26	**Guns**	**Defense** 3760-3769 Guided missiles and space vehicles and parts 3795-3795 Tanks and tank components 3480-3489 Ordnance & accessories
27	**Gold**	**Precious Metals** 1040-1049 Gold & silver ores
28	**Mines**	**Non-Metallic and Industrial Metal Mining** 1000-1009 Metal mining 1010-1019 Iron ores 1020-1029 Copper ores 1030-1039 Lead and zinc ores 1050-1059 Bauxite and other aluminum ores 1060-1069 Ferroalloy ores 1070-1079 Mining 1080-1089 Metal mining services 1090-1099 Misc metal ores 1100-1119 Anthracite mining 1400-1499 Mining and quarrying nonmetallic minerals
29	**Coal**	**Coal** 1200-1299 Bituminous coal and lignite mining
30	**Oil**	**Petroleum and Natural Gas** 1300-1300 Oil and gas extraction 1310-1319 Crude petroleum & natural gas 1320-1329 Natural gas liquids 1330-1339 Petroleum and natural gas 1370-1379 Petroleum and natural gas 1380-1380 Oil and gas field services 1381-1381 Drilling oil & gas wells 1382-1382 Oil & gas field exploration services 1389-1389 Misc oil & gas field services 2900-2912 Petroleum refining 2990-2999 Misc products of petroleum & coal
31	**Util**	**Utilities** 4900-4900 Electric, gas & sanitary services 4910-4911 Electric services 4920-4922 Natural gas transmission 4923-4923 Natural gas transmission & distribution 4924-4925 Natural gas distribution 4930-4931 Electric and other services combined 4932-4932 Gas and other services combined 4939-4939 Misc combination utilities 4940-4942 Water supply
32	**Telcm**	**Communication**

		4800-4800 Communications 4810-4813 Telephone communications 4820-4822 Telegraph and other message communication 4830-4839 Radio & TV broadcasters 4840-4841 Cable and other pay TV services 4880-4889 Communications 4890-4890 Communication services (Comsat) 4891-4891 Cable TV operators 4892-4892 Telephone interconnect 4899-4899 Misc communication services
33	**PerSv**	**Personal Services** 7020-7021 Rooming and boarding houses 7030-7033 Camps and recreational vehicle parks 7200-7200 Services - personal 7210-7212 Services - laundry, cleaning & garment services 7214-7214 Services - diaper service 7215-7216 Services - coin-operated cleaners, dry cleaners 7217-7217 Services - carpet & upholstery cleaning 7219-7219 Services - Misc laundry & garment services 7220-7221 Services - photographic studios, portrait 7230-7231 Services - beauty shops 7240-7241 Services - barber shops 7250-7251 Services - shoe repair shops & shoeshine parlors 7260-7269 Services - funeral service & crematories 7270-7290 Services – Misc 7291-7291 Services - tax return 7292-7299 Services - Misc 7395-7395 Services - photofinishing labs (School pictures) 7500-7500 Services - auto repair, services & parking 7520-7529 Services - automobile parking 7530-7539 Services - automotive repair shops 7540-7549 Services - automotive services, except repair (car washes) 7600-7600 Services - Misc repair services 7620-7620 Services - Electrical repair shops 7622-7622 Services - Radio and TV repair shops 7623-7623 Services - Refrigeration and air conditioning service & repair shops 7629-7629 Services - Electrical & electronic repair shops 7630-7631 Services - Watch, clock and jewelry repair 7640-7641 Services - Reupholster & furniture repair 7690-7699 Services - Misc repair shops & related services 8100-8199 Services - legal 8200-8299 Services - educational 8300-8399 Services - social services 8400-8499 Services - museums, art galleries, botanical and zoological gardens 8600-8699 Services - membership organizations 8800-8899 Services - private households 7510-7515 Services - truck & auto rental and leasing
34	**BusSv**	**Business Services** 2750-2759 Commercial printing 3993-3993 Signs & advertising specialties 7218-7218 Services - industrial launderers 7300-7300 Services - business services 7310-7319 Services - advertising 7320-7329 Services - consumer credit reporting agencies, collection services 7330-7339 Services - mailing, reproduction, commercial art & photography 7340-7342 Services - services to dwellings & other buildings 7349-7349 Services - building cleaning & maintenance 7350-7351 Services - Misc equipment rental and leasing 7352-7352 Services - medical equipment rental and leasing 7353-7353 Services - heavy construction equipment rental and leasing 7359-7359 Services - equipment rental and leasing 7360-7369 Services - personnel supply services 7374-7374 Services - computer processing, data preparation and processing 7376-7376 Services - computer facilities management service 7377-7377 Services - computer rental and leasing 7378-7378 Services - computer maintenance and repair 7379-7379 Services - computer related services 7380-7380 Services - Misc business services 7381-7382 Services - security 7383-7383 Services - news syndicates 7384-7384 Services - photofinishing labs 7385-7385 Services - telephone interconnect systems 7389-7390 Services - Misc business services 7391-7391 Services - R&D labs 7392-7392 Services - management consulting & P.R. 7393-7393 Services - detective and protective (ADT) 7394-7394 Services - equipment rental & leasing 7396-7396 Services - trading stamp services 7397-7397 Services - commercial testing labs

		7399-7399 Services - business services 7519-7519 Services - utility trailer & recreational vehicle rental 8700-8700 Services - engineering, accounting, research, management 8710-8713 Services - engineering, accounting, surveying 8720-8721 Services - accounting, auditing, bookkeeping 8730-8734 Services - research, development, testing labs 8740-8748 Services - management, public relations, consulting 8900-8910 Services - Misc 8911-8911 Services - Misc engineering & architect 8920-8999 Services - Misc 4220-4229 Public warehousing and storage
35	**Hardw**	**Computers** 3570-3579 Computer & office equipment 3680-3680 Computers 3681-3681 Computers - mini 3682-3682 Computers - mainframe 3683-3683 Computers - terminals 3684-3684 Computers - disk & tape drives 3685-3685 Computers - optical scanners 3686-3686 Computers - graphics 3687-3687 Computers - office automation systems 3688-3688 Computers - peripherals 3689-3689 Computers - equipment 3695-3695 Magnetic and optical recording media
36	**Softw**	**Computer Software** 7370-7372 Services - computer programming and data processing 7375-7375 Services - information retrieval services 7373-7373 Computer integrated systems design
37	**Chips**	**Electronic Equipment** 3622-3622 Industrial controls 3661-3661 Telephone and telegraph apparatus 3662-3662 Communications equipment 3663-3663 Radio & TV broadcasting & communications equipment 3664-3664 Search, navigation, guidance systems 3665-3665 Training equipment & simulators 3666-3666 Alarm & signaling products 3669-3669 Communication equipment 3670-3679 Electronic components & accessories 3810-3810 Search, detection, navigation, guidance, aeronautical & nautical systems, instruments & equipment 3812-3812 Search, detection, navigation, guidance, aeronautical & nautical systems & instruments
38	**LabEq**	**Measuring and Control Equipment** 3811-3811 Engr laboratory and research equipment 3820-3820 Measuring and controlling equipment 3821-3821 Laboratory apparatus and furniture 3822-3822 Automatic controls for regulating residential & commercial environments & appliances 3823-3823 Industrial measurement instruments & related products 3824-3824 Totalizing fluid meters & counting devices 3825-3825 Instruments for measuring & testing of electricity & electrical instruments 3826-3826 Lab analytical instruments 3827-3827 Optical instruments and lenses 3829-3829 Misc measuring and controlling devices 3830-3839 Optical instruments and lenses
39	**Paper**	**Business Supplies** 2520-2549 Office furniture and fixtures 2600-2639 Paper and allied products 2670-2699 Paper and allied products 2760-2761 Manifold business forms 3950-3955 Pens, pencils & other artists' supplies
40	**Boxes**	**Shipping Containers** 2440-2449 Wood containers 2640-2659 Paperboard containers, boxes, drums, tubs 3220-3221 Glass containers 3410-3412 Metal cans and shipping containers
41	**Trans**	**Transportation** 4000-4013 Railroads, line-haul operating 4040-4049 Railway express service 4100-4100 Local & suburban transit & interurban highway passenger transportation 4110-4119 Local & suburban passenger transportation 4120-4121 Taxicabs 4130-4131 Intercity & rural bus transportation (Greyhound) 4140-4142 Bus charter service

		4150-4151 School buses
		4170-4173 Motor vehicle terminals & service facilities
		4190-4199 Misc transit and passenger transportation
		4200-4200 Trucking & warehousing
		4210-4219 Trucking & courier services, except air
		4230-4231 Terminal & joint terminal maintenance
		4240-4249 Transportation
		4400-4499 Water transport
		4500-4599 Air transportation
		4600-4699 Pipelines, except natural gas
		4700-4700 Transportation services
		4710-4712 Freight forwarding
		4720-4729 Arrangement of passenger transportation
		4730-4739 Arrangement of transportation of freight and cargo
		4740-4749 Rental of railroad cars
		4780-4780 Misc services incidental to transportation
		4782-4782 Inspection and weighing services
		4783-4783 Packing and crating
		4784-4784 Misc fixed facilities for vehicles
		4785-4785 Motor vehicle inspection
		4789-4789 Misc transportation services
42	**Whlsl**	**Wholesale**
		5000-5000 Wholesale - durable goods
		5010-5015 Wholesale - automotive vehicles & automotive parts & supplies
		5020-5023 Wholesale - furniture and home furnishings
		5030-5039 Wholesale - lumber and construction materials
		5040-5042 Wholesale - professional and commercial equipment and supplies
		5043-5043 Wholesale - photographic equipment & supplies
		5044-5044 Wholesale - office equipment
		5045-5045 Wholesale - computers & peripheral equipment & software
		5046-5046 Wholesale - commercial equipment
		5047-5047 Wholesale - medical, dental & hospital equipment
		5048-5048 Wholesale - ophthalmic goods
		5049-5049 Wholesale - professional equipment and supplies
		5050-5059 Wholesale - metals and minerals, except petroleum
		5060-5060 Wholesale - electrical goods
		5063-5063 Wholesale - electrical apparatus and equipment
		5064-5064 Wholesale - electrical appliance, TV and radio sets
		5065-5065 Wholesale - electronic parts & equipment
		5070-5078 Wholesale - hardware, plumbing & heating equipment
		5080-5080 Wholesale - machinery, equipment & supplies
		5081-5081 Wholesale - machinery & equipment (?)
		5082-5082 Wholesale - construction and mining machinery &equipment
		5083-5083 Wholesale - farm and garden machinery & equipment
		5084-5084 Wholesale - industrial machinery & equipment
		5085-5085 Wholesale - industrial supplies
		5086-5087 Wholesale - service establishment machinery & equipment (?)
		5088-5088 Wholesale - transportation equipment, except motor vehicles
		5090-5090 Wholesale - Misc durable goods
		5091-5092 Wholesale - sporting goods & toys
		5093-5093 Wholesale - scrap and waste materials
		5094-5094 Wholesale - jewelry, watches, precious stones & metals
		5099-5099 Wholesale - durable goods
		5100-5100 Wholesale - nondurable goods
		5110-5113 Wholesale - paper and paper products
		5120-5122 Wholesale - drugs & drug proprietaries
		5130-5139 Wholesale - apparel, piece goods & notions
		5140-5149 Wholesale - groceries & related products
		5150-5159 Wholesale - farm product raw materials
		5160-5169 Wholesale - chemicals & allied products
		5170-5172 Wholesale - petroleum and petroleum products
		5180-5182 Wholesale - beer, wine & distilled alcoholic beverages
		5190-5199 Wholesale - Misc nondurable goods
43	**Rtail**	**Retail**
		5200-5200 Retail - retail-building materials, hardware, garden supply
		5210-5219 Retail - lumber & other building materials
		5220-5229 Retail
		5230-5231 Retail - paint, glass & wallpaper stores
		5250-5251 Retail - hardware stores
		5260-5261 Retail - nurseries, lawn & garden supply stores
		5270-5271 Retail - mobile home dealers
		5300-5300 Retail - general merchandise stores
		5310-5311 Retail - department stores
		5320-5320 Retail - general merchandise stores (?)
		5330-5331 Retail - variety stores
		5334-5334 Retail - catalog showroom
		5340-5349 Retail
		5390-5399 Retail - Misc general merchandise stores
		5400-5400 Retail - food stores
		5410-5411 Retail - grocery stores
		5412-5412 Retail - convenience stores

		5420-5429 Retail - meat & fish markets 5430-5439 Retail - fruit and vegetable markets 5440-5449 Retail - candy, nut & confectionary stores 5450-5459 Retail - dairy products stores 5460-5469 Retail - bakeries 5490-5499 Retail - Misc food stores 5500-5500 Retail - automotive dealers and gas stations 5510-5529 Retail - automotive dealers 5530-5539 Retail - automotive and home supply stores 5540-5549 Retail - gasoline service stations 5550-5559 Retail - boat dealers 5560-5569 Retail - recreation vehicle dealers 5570-5579 Retail - motorcycle dealers 5590-5599 Retail - automotive dealers 5600-5699 Retail - apparel & accessory stores 5700-5700 Retail - home furniture and equipment stores 5710-5719 Retail - home furnishings stores 5720-5722 Retail - household appliance stores 5730-5733 Retail - radio, TV and consumer electronic stores 5734-5734 Retail - computer and computer software stores 5735-5735 Retail - record and tape stores 5736-5736 Retail - musical instrument stores 5750-5799 Retail 5900-5900 Retail - Misc 5910-5912 Retail - drug & proprietary stores 5920-5929 Retail - liquor stores 5930-5932 Retail - used merchandise stores 5940-5940 Retail - Misc 5941-5941 Retail - sporting goods stores & bike shops 5942-5942 Retail - book stores 5943-5943 Retail - stationery stores 5944-5944 Retail - jewelry stores 5945-5945 Retail - hobby, toy and game shops 5946-5946 Retail - camera and photographic supply stores 5947-5947 Retail - gift, novelty & souvenir shops 5948-5948 Retail - luggage & leather goods stores 5949-5949 Retail - sewing & needlework stores 5950-5959 Retail 5960-5969 Retail - non-store retailers (catalogs, etc) 5970-5979 Retail 5980-5989 Retail - fuel dealers & ice stores (Penn Central Co) 5990-5990 Retail - Misc retail stores 5992-5992 Retail - florists 5993-5993 Retail - tobacco stores and stands 5994-5994 Retail - newsdealers and news stands 5995-5995 Retail - optical goods stores 5999-5999 Misc retail stores
44	**Meals**	**Restaurants, Hotels, Motels** 5800-5819 Retail - eating places 5820-5829 Restaurants, hotels, motels 5890-5899 Eating and drinking places 7000-7000 Hotels & other lodging places 7010-7019 Hotels & motels 7040-7049 Membership hotels and lodging houses 7213-7213 Services - linen supply
45	**Banks**	**Banking** 6000-6000 Depository institutions 6010-6019 Federal reserve banks 6020-6020 Commercial banks 6021-6021 National commercial banks 6022-6022 State commercial banks - Fed Res System 6023-6024 State commercial banks - not Fed Res System 6025-6025 National commercial banks - Fed Res System 6026-6026 National commercial banks - not Fed Res System 6027-6027 National commercial banks, not FDIC 6028-6029 Misc commercial banks 6030-6036 Savings institutions 6040-6059 Banks 6060-6062 Credit unions 6080-6082 Foreign banks 6090-6099 Functions related to depository banking 6100-6100 Non-depository credit institutions 6110-6111 Federal credit agencies 6112-6113 FNMA 6120-6129 S&Ls 6130-6139 Agricultural credit institutions 6140-6149 Personal credit institutions (Beneficial) 6150-6159 Business credit institutions 6160-6169 Mortgage bankers and brokers 6170-6179 Finance lessors 6190-6199 Financial services

46	**Insur**	**Insurance** 6300-6300 Insurance 6310-6319 Life insurance 6320-6329 Accident and health insurance 6330-6331 Fire, marine & casualty insurance 6350-6351 Surety insurance 6360-6361 Title insurance 6370-6379 Pension, health & welfare funds 6390-6399 Misc insurance carriers 6400-6411 Insurance agents, brokers & service
47	**RlEst**	**Real Estate** 6500-6500 Real estate 6510-6510 Real estate operators and lessors 6512-6512 Operators - non-resident buildings 6513-6513 Operators - apartment buildings 6514-6514 Operators - other than apartment 6515-6515 Operators - residential mobile home 6517-6519 Lessors of railroad & real property 6520-6529 Real estate 6530-6531 Real estate agents and managers 6532-6532 Real estate dealers 6540-6541 Title abstract offices 6550-6553 Land subdividers & developers 6590-6599 Real estate 6610-6611 Combined real estate, insurance, etc
48	**Fin**	**Trading** 6200-6299 Security and commodity brokers, dealers, exchanges & services 6700-6700 Holding & other investment offices 6710-6719 Holding offices 6720-6722 Management investment offices, open-end 6723-6723 Management investment offices, closed-end 6724-6724 Unit investment trusts 6725-6725 Face-amount certificate offices 6726-6726 Unit investment trusts, closed-end 6730-6733 Trusts 6740-6779 Investment offices 6790-6791 Misc investing 6792-6792 Oil royalty traders 6793-6793 Commodity traders 6794-6794 Patent owners & lessors 6795-6795 Mineral royalty traders 6798-6798 REIT 6799-6799 Investors, NEC
49	**Other**	**Almost Nothing** 4950-4959 Sanitary services 4960-4961 Steam & air conditioning supplies 4970-4971 Irrigation systems 4990-4991 Cogeneration - SM power producer

Table A2: Table of Commodity futures Further Details

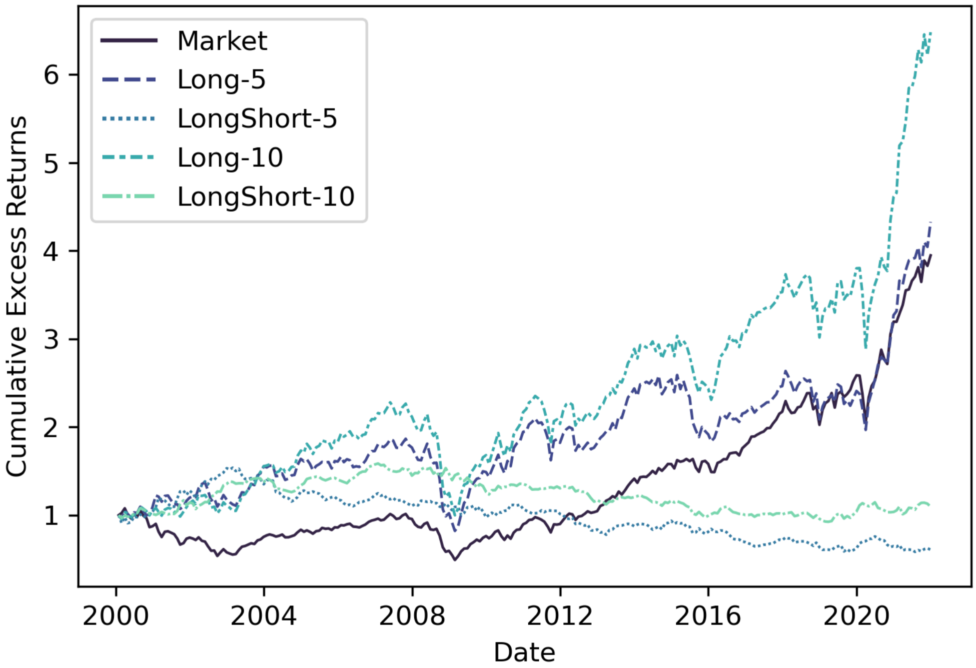
Table A2: The table present the full list of commodity futures utilised for the analysis. Abbr. is the abbreviation utilised throughout our analysis, Ticker is the security ticker utilised by Bloomberg, and the exchange list at where the respective commodity future is traded.

Commodity	Abbr.	Ticker	Exchange
Aluminium	A	LA1 Comdty	LME - London Metal Exchange
Cattle	Ca	LC1 Comdty	CME - Chicago Mercantile Exchange
Cocoa	Coc	CC1 Comdty	NYB - ICE Futures US Softs
Coffee	Cf	KC1 Comdty	NYB - ICE Futures US Softs
Coking Coal	CC	CKC1 Comdty	DCE - Dalian Commodity Exchange
Copper	Cop	HG1 Comdty	CMX - Commodity Exchange, Inc.
Crude	Cru	CL1 Comdty	NYM - New York Mercantile Exchange
Ethanol	Eth	DL1 Comdty	CBT - Chicago Board of Trade
Glass	Gl	FGL1 Comdty	ZCE - Zhengzhou Commodity Exchange
Gold	Go	GC1 Comdty	CMX - Commodity Exchange, Inc.
Hog	H	LH1 Comdty	CME - Chicago Mercantile Exchange
Iron	I	IOE1 Comdty	DCE - Dalian Commodity Exchange
Lead	L	LL1 Comdty	LME - London Metal Exchange
Lumber	Lu	LB1 Comdty	CME - Chicago Mercantile Exchange
Natural Gas	NG	NG1 Comdty	NYM - New York Mercantile Exchange
Nickel	N	LN1 Comdty	LME - London Metal Exchange
Palm Oil	PO	KO1 Comdty	MDE - Bursa Malaysia
Platinum	P	PL1 Comdty	NYM - New York Mercantile Exchange
Polyethelene	Pe	POL1 Comdty	DCE - Dalian Commodity Exchange
Polyvinyl Chloride	PvC	PVC1 Comdty	DCE - Dalian Commodity Exchange
Pure Terephthalic Acid	PTA	PT1 Comdty	ZCE - Zhengzhou Commodity Exchange
Rice	R	RR1 Comdty	CBT - Chicago Board of Trade
Silver	Si	SI1 Comdty	CMX - Commodity Exchange, Inc.
Soy	So	S 1 Comdty	CBT - Chicago Board of Trade
Sugar	Su	SB1 Comdty	NYB - ICE Futures US Softs
Tin	T	LT1 Comdty	LME - London Metal Exchange
Wheat	W	W 1 Comdty	CBT - Chicago Board of Trade

A.2 Additional Figures

Figure A1: Cumulative Excess Returns of Strategies and Market

Figure A1: The figure present the excess cumulative returns of the tested generic trading strategies compared to that of the US market. $LongShort - x$ is a strategy that goes long (short) the top (bottom) x estimated performing industries based on the calculated factor loadings in each period. $Long - x$ is a strategy that goes long the top x estimated performing industries based on the calculated factor loadings in each period.



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