FINANCIAL MARKET INNOVATION AND PRODUCT INNOVATION: EVIDENCE FROM COMMODITY FUTURES MARKETS AND STOCK MARKETS

by

Lingfei Kong

A dissertation submitted to the faculty of
The University of North Carolina at Charlotte
in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in
Business Administration

Charlotte

2021

Approved by:

____
Dr. Yufeng Han

____
Dr. I-Hsuan Ethan Chiang

____
Dr. Christopher M. Kirby

____
Dr. Arthur Zillante

ABSTRACT

LINGFEI KONG. Financial Market Innovation and Product Innovation: Evidence from Commodity Futures Markets and Stock Markets (Under the direction of DR. YUFENG HAN)

This dissertation contains three connected essays that feature financial market innovation and product market innovation. Two essays feature return predictability in commodity futures, which have been financialized during the past two decades. One essay studies the relation between CEO's external job market tournament and product innovation in the stock market. The first essay uses machine learning tools to study the serial dependence (lead-lag relations) of commodity futures returns. We use LASSO to select the predictors because the number of independent variables is large relative to the number of data points. We find significant full-sample and out-of-sample predictability. In the full sample, we find that LASSO can identify a sparse set of predictors that either come from economically linked commodities or are likely driven by excessive speculative trading. The out-of-sample forecasts based on LASSO generate statistically and economically large performance. When we use more complex machine learning models such as neural networks and regression trees to forecast commodity futures returns, the out-of-sample performance is worse than LASSO portfolios, suggesting that nonlinearities and interactions do not appear substantial in the data. We also find that index trading due to financialization drives the excess comovement among commodity futures. The second essay identifies a trend factor in commodity futures markets that exploits the short-, intermediate-, and long-run moving averages of settlement price in commodity futures markets. The trend factor generates statistically and economically large returns during the sample period 2004-2019. It beats the popular momentum factor by more than five times the Sharpe ratio and less downside risk. The trend factor cannot be explained by existing factor models and is priced cross-sectionally. Then we discover that the trend factor can be explained by funding liquidity measured by TED spread. Overall, the results indicate that there are significant economic benefits from using the information on historical prices in commodity futures markets. The third essay examines how the tournament-like progression in the CEO labor market influences corporate innovation strategies. By exploiting a text-based proxy for product innovation based on product descriptions from 10-Ks, we find that industry tournament incentives (ITIs) positively affect product innovation. We then explore the trade-off effects of ITIs on product innovation created through long-term patenting technologies and short-term "routine" product development. We discover that ITIs strengthen routine product development activities but decrease patent-based innovation.

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to my committee chair, mentor, and coauthor Yufeng Han for his invaluable guidance and advice. He has played a vital role in my thesis progress and job market search. I also would like to thank my dissertation committee members Ethan Chiang, Chris Kirby, and Artie Zillante for helping me with my thesis and job search. I am thankful to Gene Lai, Dolly King, Qianqiu Liu, and David Mauer for their valuable job market advice and smart job search strategy. I thank my two coworkers Gunratan Lonare and Ahmet Nart who are also my coauthors.

I thank Belk College Finance Faculty for their excellent teaching, top-tier research support (e.g., high-quality research seminars, chances of collaborating with faculty members, and generous database subscriptions), and insightful comments on my research papers. I thank my fellow graduate students, friends, fur friends for their support and encouragement. I give special thanks to my friend B for his help with writing this thesis and his kindness and encouragement.

I thank my parents for their encouragement and push on my graduation and my job market search. They've been pushing me to graduate in Spring 2021 and become financially independent.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

This dissertation contains three connected essays that feature financial market innovation and product market innovation. Two essays feature return predictability in commodity futures, which have been financialized during the past two decades. One essay studies the relation between CEO's external job market tournament and product innovation in the stock market.

Commodity futures contracts are agreements to buy or sell a predetermined quantity of a commodity at a specified price on a particular date in the future. Historically, commodity futures were primarily used by farmers and producers to lock in the price and reduce the risk of financial losses from price changes. Over the past two decades, financial institutions such as hedge funds, swap dealers, and mutual funds have dramatically increased their exposure to commodities. The advent of commodity futures ETFs and ETNs also gives individual investors easy access to commodity futures. According to BarclayHedge, the asset under management for the managed futures has grown from $95.7 billion to $318.4 billion from 2003 to 2019.[1] This phenomenon is called "financialization" by researchers (e.g., Tang and Xiong, 2012; Basak and Pavlova, 2016), and has received extensive attention from researchers and practitioners. The first two essays focus on return predictability during the post financialization period (2004-2019) when investors have easier access to commodity futures than before. Researchers find that during financialization period, commodity futures markets have been more liquid and have experienced an increasing speculative trading (e.g., Gong, Gozluklu, and Kima, 2020). The highly liquid commodity futures

[1] See the data from the website of BarclayHedge https://www.barclayhedge.com/solutions/assets-under-management/cta-assets-under-management/CTA-industry/

markets during the financialization period make our proposed long-short trading strategy implementable.

Compared with the traditional asset classes such as stocks and bonds, commodity futures have the following advantages as investment tools. First, commodity futures' returns are not very correlated to the returns of other asset instruments such as bonds, foreign currencies, and stocks, and thus they provide diversification benefits to investors. Second, commodity futures can be easily leveraged. The initial margin is only a proportion of the market value. Finally, commodity trading advisors can long or short futures contracts with equal ease. In contrast, stocks and bonds need to be borrowed before they can be shorted, and it is often costly to borrow and is subject to sudden recall, thus making shorting very costly and risky. In addition, short positions via put options or inverse ETFs tend to be relatively costly and inefficient. The advantages of trading futures should make it much easier to implement the trading strategies discussed in this thesis.

Chapter III focuses on product innovation strategies. The competition from rivals and discerning customers with rapidly changing preferences force firms to modify and develop their products constantly for their survival and to earn more market shares and profits. Product innovation is crucial for a firm's survival, since it builds entry barriers, maintains customer loyalty, protects against imitation, and provides penetration to the market (Soete, 1981; Clark and Guy, 1998; Boehe and Cruz, 2010). New technologies and the improvement of existing technologies or product/service quality can also lead to firm growth (e.g., Coad and Rao, 2008). We discover that ITIs strengthen routine product development activities but decrease patent-based innovation, suggesting that CEOs conduct more incremental product development than revolutionary technological innovation to win the tournament prize so that they can move up in a shorter time.

CHAPTER I THE SERIAL DEPENDENCE OF THE COMMODITY FUTURES RETURNS: A MACHINE LEARNING APPROACH

I.1 Introduction

This essay examines the predictability of commodity futures returns. Specifically, we examine the serial dependence (lead-lag relations) of commodity futures returns using the commodity futures' own lagged returns as well as lagged returns of other commodity futures. We focus on the post-financialization period (2004-2019) when commodity futures become a popular investment asset class and the futures markets become more liquid than before. The inclusion of the broad set of lagged returns is motivated by the following arguments.

First, many futures have economic links that can drive the lead-lag relations among futures returns. For instance, heating oil is refined from crude oil, so it is possible that the lagged returns of crude oil futures can be tied to the returns of heating oil futures; Corns and soybean meals are the primary feeds for the livestock such as pigs and cows, thus the returns of corn and soybean futures can impact the returns of lean hogs and live cattle futures at some stage of the production; Crops such as corn and soybeans are used to produce biofuels, which are substitutes for fossil fuels such as crude oil, so crude oil futures prices can be related to grain futures prices. Mensi, Hammoudeh, Nguyen, and Yoon (2014) find significant spillovers among grain and energy commodity prices by studying the lead-lag relations of the returns and volatilities of these commodities. [2]

[2] Also see Chen, Kuo, and Chen (2010); Nazlioglu and Soytas (2011, 2012); Reboredo (2012); Wang, Wu, and Yang (2014), among others. Many of these studies use spot prices rather than futures prices to examine the spillover between energy and grain commodities. However, their conclusions still support our arguments because researchers often use the nearby futures price to proxy spot price.

Second, the rising trading activities by financial institutions and retail investors can either weaken or strengthen these effects, or even introduce new relations that are not driven by any economic links. Unlike the producers/merchants who use futures contracts to lock in the price of their products or inputs, these traders generally do not have physical exposure to the commodities but use commodity futures as investment tools, and thus are generally considered speculators. Researchers find that the proliferation of speculative trading has caused price distortion and excessive price comovement. For example, Tang and Xiong (2012) find that since 2004 when financial institutions significantly increased their positions on commodity futures, the prices of non-energy commodity futures have become increasingly correlated with oil futures, and the correlations are stronger for commodities that are included in the broadly traded commodity indices than for non-indexed commodities.[3]

So far previous studies have focused on either identifying the contemporaneous relation between the commodity futures or the spillovers among commodities within the same sector or between sectors, especially in the energy or agriculture sector. Our study is a natural extension to these studies as we examine the lead-lag relations among a wide selection of commodity futures returns and exploit predictability. The issue of return predictability of commodity futures becomes increasingly important given that commodity futures have become an important asset class for investment. There are studies examining whether including commodity futures to traditional asset classes adds value to investors (e.g, You and Daigler, 2013; Cotter, Eyiah-Donkor, and Potì, 2017; Gao and Nardari, 2018), the predictability of broad commodity indices (e.g., Gargano and

[3] Ohashi and Okimoto (2016) find that the contemporaneous correlations between commodity prices after orthogonalizing macroeconomic fundamentals have been increased since around 2000. Moreover, the increased correlations do not exist in non-indexed commodities. Le Pen and Sevi (2018) find that there are strong correlations between commodity prices across different sectors that have no economic link, such as a positive correlation between live cattle and copper and negative correlation between silver and soybeans.

Timmermann 2014; Lutzenberger, 2014), and the predictability in individual commodity futures or sectors (e.g., Wang 2001; Guidolin and Pedio, 2020; Hollstein, Prokopczuk, Tharann, and Simen, 2020). As far as the authors know, this is the first paper to study return predictability based on the lead-lag relations among a broad set of commodity futures.

We analyze how the returns of individual commodity futures are affected by the lagged returns of a wide selection of commodity futures. Specifically, we use the first and second lagged returns of all the commodity futures as the candidate predictors. Compared with the number of observations used to run predictive regressions, the number of predictors is large.[4] In OLS regressions, a large number of explanatory variables can cause overfitting problems, i.e., increase the R-squared of the in-sample regression but generate poor out-of-sample forecasts. To overcome overfitting, we use such machine learning techniques as LASSO (Least Absolute Shrinkage and Selection Operator) to select the potentially important predictors. Machine learning techniques have become increasingly popular in the finance literature, and LASSO is one of the most widely used methods because it can select variables from a large range of predictors. For example, Chinco, Clark-Joseph, and Ye (2019) employ LASSO to forecast stock returns using a large set of lagged stock returns in an intraday setting. Miao, Ramchander, Wang, and Yang (2017) and Zhang, Ma, and Wang (2019) use LASSO (or elastic net) to forecast crude oil prices. Hollstein et al. (2020) use forecast combination and elastic net to select a wide range of macroeconomic variables for the spot returns of commodities.[5]

[4] The in-sample analysis has the largest number of observations 192, while the number of candidate predictors is $27 \times 2 = 54$. In the one-step predictive regressions, the number of candidate predictors is 54, and the estimation window is 60 months.

[5] Also see Rapach, Strauss, and Zhou (2013, 2019), Freyberger, Neuhierl, and Weber (2020), Gu, Kelly, and Xiu (2019), among others.

To get a glimpse of the big picture of the predictive ability of the lagged commodity futures returns, we first estimate the LASSO regression using the whole sample period (January 2004−December 2019). We find that LASSO selects a sparse set of predictors. Some predictors reflect the economic links between the underlying commodities. For instance, there is a strong lead-lag relation between lean hogs and grain futures, because grains are the main food for pigs. However, some lead-lag relations are of no apparent economic links, which are likely due to the increasing speculative trading activities that drive the futures price away from the fundamental.

Next, we examine the out-of-sample predictability of the lagged returns based on a 60-month rolling estimation window. We form a long-short spread portfolio that longs (shorts) the commodity futures with the highest(lowest) forecasted returns. We find that the LASSO forecasts can generate large gains, both statistically and economically. For example, the long-short spread portfolio generates an average annualized excess return of 15.15% and a Sharpe ratio of 0.93. In addition, the annualized alpha is 16.61% after adjusting for an average factor, a basis factor, a momentum factor (Bakshi, Gao, and Rossi, 2019), and a hedging pressure factor (Kang, Rouwenhorst, and Tang, 2020). The performance is much better than that of the two benchmark portfolios, both of which yield insignificant returns. One uses the rolling historical average returns to forecast, and the other uses OLS forecasts with all the lagged returns as predictors. We further construct timing portfolios that long the commodity futures with positive return forecasts and short those with negative return forecasts. The LASSO timing portfolios generate an average annualized excess return of 6.15%, a Sharpe ratio of 0.72.[6] By contrast, the timing portfolios based on the

[6] The return to the timing strategy in our paper is $\frac{1}{N}(\sum_{\hat{r}_{it}\geq 0} r_{it} - \sum_{\hat{r}_{it}<0} r_{it})$, where N is the number of commodity futures, $\hat{r}_{it}$ is the forecasted returns. Goyal and Jegadeesh (2018) multiply the above return by 2 to make the position of the timing strategy and the single-sort strategy comparable so that the total position is equal to $2 for both strategies. However, our goal is not to compare the timing strategy with the single-sort strategy. If we do the

prevailing mean and OLS forecasts are neither statistically nor economically significant. We also test other benchmark models such as forecasts based on autoregressions, hedging pressures, momentum, and basis, and none of them outperform the LASSO forecasts. The superior performance of the LASSO forecasts demonstrates the predictive power of lagged returns and the effectiveness of LASSO in an out-of-sample setting. When we use more complex machine learning models such as neural networks and regression trees to forecast commodity futures returns, the out-of-sample performance is worse than LASSO portfolios, suggesting that nonlinearities and interactions do not appear substantial in the data.

Finally, we test the hypothesis that financialization sets off the excess comovement among commodity futures in several ways. We first separate the commodity futures into indexed futures if they are included in the two major commodity indices (Bloomberg Commodity Index (BCOM) and S&P Goldman Sachs Commodity Index (GSCI)) and non-indexed ones otherwise. We find that the LASSO portfolios constructed from the indexed futures produce economically large and statistically significant out-of-sample returns in both the single-sort and timing strategies, whereas those from the non-indexed futures no longer yield any significant returns. We then show that LASSO picks up many lagged returns after the inception of the two major commodity indices, providing another evidence supporting the hypothesis.

One closely related study is Da, Tang, and Tao (2020) who find that financialization can result in sentiment spillover across indexed commodities, causing price pressure and subsequent price reversals at daily level for indexed commodity futures, but not for non-indexed futures. Different from Da et al. (2020) who focus on the autocorrelation, we study the lead-lag relations

same adjustment as Goyal and Jegadeesh (2018), the annualized excess returns of the timing portfolios will be $2 \times 6.15\% = 12.3\%$.

both within each commodity futures and across different commodity futures. Another difference is that we focus on the economic significance of the serial dependence. Last but not the least, the majority of CTAs (Commodity trading advisors) are trend-followers who chase time-series momentum or other trend signals, which have been proven to be profitable (e.g., Szakmary, Shen, and Sharma, 2010; Moskowitz, Ooi, and Pedersen, 2012; Bianchi, Drew, and Fan, 2016; Han, Hu, and Yang, 2016), and momentum is likely to be induced by the lead-lag relations among the securities (Lewellen, 2002; DeMiguel, Nogales, and Uppal, 2014).

Chapter I contributes to existing studies in multiple ways. First, the majority of the literature after financialization studies the comovement among commodity futures in the context of contemporaneous relations rather than the lead-lag relations. Moreover, most papers regarding return predictability in commodity futures focus on the futures' own past returns or other characteristics but ignore the cross-serial correlations. As far as we can tell, this paper is the first to analyze the predictability of the lagged futures returns that allows each individual commodity futures' return to respond to the lagged returns for all commodity futures, thereby accommodating a large dimension of commodity links, both direct and indirect. Second, we use machine learning techniques to overcome the potential overfitting problem. With a great number of predictors, OLS estimation is subject to overfitting. Third, we find that incorporating the lagged returns of commodity futures can help to forecast the returns for individual commodity futures and construct profitable trading strategies. The performance of the long-only futures indices has been lackluster in the last decade.[7] By contrast, the actively constructed single-sort or timing strategies based on the LASSO generate both statistically and economically large out-of-sample returns.

[7] Based on the data from Bloomberg terminal, from January 2009 to December 2019, the average annual return of the S&P GSCI (Goldman Sachs Commodity Index) excess return index is -2.63%, the average annual return of the BCOM (Bloomberg Commodity Index) excess return index is –2.40%.

I.2 Data and Variable Definitions

We study 27 commodity futures that are traded actively in the US. The data are collected from Bloomberg. The 27 commodity futures cover five main sectors, namely, grains, softs, energy, livestock, and metal. There are 8 grains futures, 7 softs futures, 3 livestock futures, 4 energy futures, and 5 metal futures in the sample.[8] The sample period is January 2004-December 2019. Following Szymanowsk, Roon, Goorbergh, and Nijman (2014), Boons and Prado (2019), we calculate monthly excess returns on a fully collateralized long position for each futures,

$$R_{fut,t+1}^{T_n} = \frac{F_{t+1}^{T_n}}{F_t^{T_n}} - 1 \tag{2.1}$$

Where $F_{t+1}^{T_n}$ is the settlement price of the first-nearest futures contract held in month t that expires *after* month $t+2$, and T_n is the expiration date. When the contract is about to expire within two months, we then close the current contract and open the contract with the next expiration month, which becomes the new first-nearest futures contract that expires after two months. In this way, we ensure the liquidity of the trading while avoid holding contracts close to maturity when the settlement prices become less informative. For example, consider our return calculation with respect to platinum futures in August 2018 ($t+1=$August 2018). At the end of July 2018 (t), the three contracts with the nearest maturities are expired on October 2018, January 2019, and April 2019, respectively. So the first nearest contract that expires after September 2018 ($t+2$) is the October 2018 contract, and thus we open a position of the October 2018 contract and hold it until August 2018. At the end of August 2018 ($t=$ August 2018, $t+1$ becomes September 2018), we

[8] From 2005 to 2006, the ticker for the gasoline futures was changed from HU to RB gradually. On December 2006, HU was changed completely by RB. So before 2006 we use the settlement prices of HU contracts, after 2006 we use those of RB contracts.

need to close the October 2018 contract because it expires before the end of October. At the same time, we open the January 2019 contract and hold it until November 2018. Thus, the return on August is based on the October 2018 contract and the return on September is based on the January 2019 contract.

Table 1 summarizes the excess returns for the 27 commodity futures studied in this paper by sectors from January 2004 to December 2019. It also includes the ticker symbol in Bloomberg. In general, metal futures and a few energy futures exhibit positive average returns in the sample period, many agriculture futures have negative average returns. The returns are highly volatile. The annualized standard deviations of most futures are around 30%. Live cattle, feeder cattle, and gold are the least volatile futures with annualized standard deviations less than 20%. Because of the large variation of returns, many of the average returns are not statistically significant after the financialization period. The average return for natural gas is even significantly negative. These results are in line with the recent poor performance of the commodity futures market.

I.3 Methodology

I.3.1 The LASSO

The specification for testing the predictability of lagged futures returns for the i^{th} futures is given by:

$$y_i = a_i^* l_T + Xb_i^* + \varepsilon_i \tag{3.1}$$

Where

$$y_i = [r_{i,1}, \cdots, r_{i,T}]' \tag{3.2}$$

$$X = [x_1, \cdots x_N, x_{N+1}, \cdots, x_{2N}] \tag{3.3}$$

$$x_j = [r_{j,0}, \cdots, r_{j,T-1}]\,', \; j = 1, \cdots, N \;, \tag{3.4}$$

$$x_j = [r_{j,-1}, \cdots, r_{j,T-2}]\,', \; j = N+1, \cdots, 2N \tag{3.5}$$

$$b_i^* = [b_{j,1}^*, \cdots, b_{j,N}^*, b_{j,N+1}^*, \cdots, b_{j,2N}^*]' \tag{3.6}$$

$$\varepsilon_i = [\varepsilon_{i,1}, \cdots, \varepsilon_{i,T}]' \tag{3.7}$$

$r_{i,t}$ is the month-t excess return on commodity futures i, l_T is a T-vector of ones, T is the usable number of monthly observations for commodity futures i, N is the number of individual commodity futures used to predict the returns for futures i, and ε_i is the residual. Equation (3.1) includes the first and second lagged returns for all the commodity futures available, thus allowing for the links among commodities. In our sample, the number of regressors is 54, and T is 192 in the full-sample, 60 in the rolling out-of-sample regressions. With a large amount of regressors, OLS can reduce the in-sample mean squared error but often results in large out-of-sample mean squared error. This phenomenon is known as overfitting. To reduce overfitting, Tibshirani (1996) introduced the LASSO. LASSO solves for the minimum square error of the model with the constraint that the summation of the absolute values of the regression coefficients is smaller than a specified shrinkage parameter. If the shrinkage parameter is small enough, some of the regression coefficients will become 0, thus only a subset of regressors is selected. For Equation (3.1), the optimization problem for the LASSO is:

$$\min_{a_i \in R, b_i \in R^n} \; \| y_i - a_i l_{(T)} - X b_i \|_2^2 \;, \text{ subject to } \|b_i\|_1 \le s \tag{3.8}$$

where

$$\| z \|_2 = (\sum_{t=1}^{T} z_t^2)^{0.5}, z = [z_1 \cdots z_T]' \tag{3.9}$$

$$\| b_i \|_1 = \sum_{j=1}^{N} | b_{i,j} |, \tag{3.10}$$

and s is the shrinkage parameter. The objective function of LASSO can also be written as:

$$\min_{a_i \in R, b_i \in R^n} \| y_i - a_i l_{(T_i)} - X b_i \|_2^2 + \lambda_i \| b_i \|_1 = RSS + \lambda_i \| b_i \|_1 \tag{3.11}$$

The first term is the residual sum of squares (RSS), the second term is an ℓ_1 penalty that shrinks the coefficient estimates of some regressors towards zero if the regularization parameter λ_i is large enough. When λ_i is 0, the objective function is the same as that for the OLS regression, and all the regressors will be selected. When λ_i goes to infinity, all the coefficient estimates will be restricted to 0.

It is critical to select a good value of the shrinkage parameter λ_i in Equation (3.11), or s in Equation (3.8). There are mainly two approaches, namely, information criteria and K-fold cross-validation. Cross-validation is the most commonly used method to select λ_i, but it is inappropriate in the time-series setting because it randomly splits the data and does not maintain the order of the observations.

Another way to select the penalty parameter is information criteria, including AIC (Akaike information criterion), (Bayesian information criterion BIC), and AICC (corrected Akaike information criterion). However, BIC is not minimax optimal, i.e., it requires a large sample to get the true model selected, more than other criteria such as AIC, and therefore it has a larger mean average squared error than AIC (Yang, 2005; Erven, Grünwald, and De Rooij, 2012). The corrected Akaike information criterion (AICC) corrects for the small sample size. The AICC is defined as:

$$AICC = AIC + \frac{2k(k+1)}{n-k-1} = 2\left(\log L_k - \frac{n}{n-p-1}\right) = \frac{RSS}{n\sigma^2} + \frac{2d}{n} + \frac{2k(k+1)}{n-k-1} \qquad (3.12)$$

Where k is the number of parameters and n is the sample size. The term after AIC corrects for small-sample bias, thus AICC avoids overfitting when the sample size is small. In this paper, we use AICC as the criteria to select the shrinkage parameter. [9]

Although LASSO can shrink the coefficients of "unimportant" predictors to zero, it also causes over-shrinkage of the magnitudes of the coefficients for the selected predictors. Efron, Johnstone, and Tibshirani (2004) suggest that after using LASSO to select the model, one can use OLS to estimate the coefficients for the selected predictors. Belloni and Chernozhukov (2013) find that the OLS post-LASSO estimator has a larger convergence rate and a smaller regulation bias than the pure LASSO estimator. So we use OLS to estimate the coefficients for the predictors selected by LASSO.

To get a glimpse of the overall lead-lag relations, we first estimate regressions via LASSO using the full sample period January 2004−December 2019. The shrinkage parameter λ_i are selected on a futures-by-futures basis via AICC. To obtain the out-of-sample forecasts, we choose the shrinkage parameter on a futures-by-futures basis in each 60-month estimation window. We will discuss the details of out-of-sample forecast construction in section I.3.2.

[9] Nevertheless, we use cross-validation to select the penalty parameter as robustness check. The results in sections 4-7 are quantitatively similar when we use cross-validation to select the penalty parameter.

I.3.2 Out-of-sample predictive regression

We estimate the out-of-sample forecasts of futures returns using rolling windows that consist of q months with one-month increment. Specifically, at the end of month $q + 1$, we estimate Equation (3.1) using the observations from month 1 (January 2004) to month q, and forecast futures returns at month $q + 1$. Then the process is repeated using the observations from month 2 (February 2004) to month $q + 1$, and repeated again until the end of sample. Suppose the LASSO identified K_q predictors, then we use the following OLS regression to estimate the coefficients for the K_q predictors:

$$\hat{r}_t = \hat{\alpha}_q + \sum_{k=1}^{K_q} \hat{\beta}_{k,q} r_{k,t-1 \text{ or } t-2}, \; t = 1, ..., q \tag{3.13}$$

The out-of-sample forecast at month $q + 1$ is given by:

$$\hat{r}_{q+1} = \hat{\alpha}_q + \sum_{k=1}^{K_q} \hat{\beta}_{k,q} r_{k,q} \tag{3.14}$$

Where $\hat{\alpha}_q$ and $\hat{\beta}_{k,q}$ are the coefficients estimated by Equation (3.13). The forecast for the next time period $q + 2$ is obtained by

$$\hat{r}_{q+2} = \hat{\alpha}_{q+1} + \sum_{k=1}^{K_{q+1}} \hat{\beta}_{k,q+1} r_{k,q+1} \tag{3.15}$$

Where $\hat{\alpha}_{q+1}$ and $\hat{\beta}_{k,q+1}$ are the LASSO estimates based on regressing $\{r_{t'}\}_{t'=2}^{q+1}$ on the selected predictors from the series.$\{r_{1t'}, r_{2t'}, \ldots, r_{Nt'}; r_{1t'-1}, r_{2t'-1}, \ldots, r_{Nt'-1}\}_{t'=1}^{q}$ We set q to be 60 months, about 1/3 of the whole sample period (192 months). By estimating the out-of-sample forecast recursively, we finally obtain 132 months out-of-sample forecasts from January 2009 to December 2019.

We also have two benchmark forecasts based on prevailing mean and OLS. The prevailing mean forecasts are the moving average returns of the past 60 months, while the OLS forecasts include all the lagged returns as the regressors in Equation (3.1). Therefore, the return forecasts based on the three methods are obtained in the same manner. The two benchmarks are widely used in the literature of return predictability in the equity market.

I.4 Full-Sample Results

In this section, we use LASSO regression to estimate Equation (3.1) for the full sample period January 2004-December 2019. The parameter estimates are shown in Table 2. The LASSO selects 82 lagged returns (out of $27 \times 54 = 1458$) as the predictors for the individual commodity futures. At least one lagged commodity futures return is selected for 18 of the 27 individual futures. After LASSO selection, we estimate OLS coefficients based on the Newey-West t-statistics with automatic lags. Based on the Newey-West t-statistics, 50 (45) of the 82 LASSO-selected lagged futures returns are significant at the 10% (5%) level. Only 6 commodity futures are affected by their own lagged returns. Among these 6 futures, only the returns for the cocoa futures are negatively affected by their own lagged returns. Others such as sugar and crude oil futures have positive autocorrelations.

There are also many other noteworthy patterns for the full-sample results. First, the relation between the lagged returns and the affected individual commodity futures returns is asymmetrical. For example, the lagged returns for lean hogs futures are selected as the predictor of wheat futures returns, but the lagged returns for wheat futures are not selected as the predictor of lean hogs futures. Second, in some cases the selected lagged returns come from the same sectors as the affected individual commodity futures. Among the 82 effects, there are 26 effects in which the futures returns and the selected lagged returns are from the same sectors. For example, the lagged returns for milk positively affect the returns for coffee, indicating that they complement each other. Third, the majority of the effects are across sectors. For instance, the lagged returns for lean hogs are positively associated with the returns for Kansas wheat, wheat, soybean, and soybean meal futures. This is probably because lean hogs consume those grains products, thus when the market demand for pork is high, the demand for these grains also increases, thus driving up the futures prices. In addition, the lagged returns for gasoline are selected as the predictor for corn futures, because corn can be used to produce ethanol, and both ethanol and gasoline are important fuels. Fourth, many selected lagged returns have no economic link with the affected individual commodity futures. For instance, the lagged returns for platinum futures are selected as the predictor of cocoa futures, and there is no economic relation between platinum and cocoa.

Some of the above results are hard to be interpreted by the economic links between the underlying commodities, but it is likely due to financialization. First, the proliferation of speculative trading can make commodities futures behave like investment assets and drive the prices away from the supply and demand of the underlying commodities. Those arguments are supported by the existing literature. For example, Ciner, Lucey, and Yarovaya (2018) find strong return and volatility spillovers among the London Metal Exchange listed industrial metal futures, and the relation is stronger during the financial crisis. They conclude that the behavior of the industrial metal futures is similar to equity and bonds and their returns are affected not only by the fundamentals but also the trading behavior of the investors. Bosch and Pradkhan (2017) find that index traders add noise to commodity futures market by decreasing the convergence rate of futures price and spot prices because they use commodity futures to build trading strategies and constantly roll over their positions. In addition, some commodity index funds invest in a basket of commodities and they have long-only exposure to commodities,[10] which can lead to comovement and risk sharing in prices and returns among commodities (Tang and Xiong, 2012). Overall, the full-sample results identify a set of sparse and sometimes unexpected predictors. Our findings of some unexpected lead-lag relations are similar to Chinco et al. (2019), who identify a set of unanticipated lagged returns as predictors for the individual stock returns during a 30-minute interval based on LASSO.

I.5 Out-of-Sample Results

In this section, we study whether incorporating the lagged returns can help to forecast the returns of individual commodity futures on an out-of-sample basis. We analyze the out-of-sample performance predictability of commodity futures' lagged return based on monthly rebalanced portfolios. The return forecasts are based on a 60-month rolling window. The out-of-sample period is from January 2009 to December 2019.[11]

I.5.1 Zero-cost spread portfolios

First, we consider zero-cost portfolios based on the sorts by the forecasted returns. For every out-of-sample month (January 2009 to December 2019), we sort individual futures by their forecasted returns and form equally-weighted portfolios using the five futures with the highest forecasted returns (High5) and the five commodity futures with the lowest forecasted returns

[10] According to ETFdb.com, as of 2019-03-29, the ETFs with the top ten largest total asset under management include three broad commodity indices. Others are ETFs that tracks the return of precious metals such as gold, silver, and platinum. The total assets for the three broad commodity indices exceed $ 5 billion.

[11] The frequency of LASSO predictors during the out-of-sample period is shown APPENDIX A. The results are mainly consistent with the full-sample results in Table 2, i.e., the frequently selected lagged returns during the out-of-sample period are usually the predictors in the full-sample.

(Low5). We then calculate the return differences between the two portfolios, which is a zero-cost portfolio that buys the High5 portfolio and sells the Low5 portfolio. The forecasts for the out-of-sample periods only use the data before the forecast month, thus we do not have any "look-ahead" bias. In addition, for some commodity futures, the only selected effect is the intercept, i.e., no lagged returns are selected as the predictors. In this case, we either regress its own return on ones to obtain the return forecast (which is simply the prevailing mean of the past returns during the estimation window), or do not include those futures when calculating the return forecasts. In the latter case, the High5 and Low5 portfolios will not include any commodities with no selected lagged returns. Our results are robust to either approach.

We compare the above strategy with two benchmark portfolios. They are similarly constructed using return forecasts from the prevailing mean and OLS, respectively. Table 3 reports the performance of the two benchmark portfolios and the two LASSO portfolios. The performance measures include the annualized mean returns, standard deviation, Sharpe ratio, and two measurements for downside risk, which are the annualized downside risk and Sortino ratio.[12] For both benchmark portfolios, the prevailing mean and OLS, the annualized average returns are insignificant, whereas the two LASSO portfolios, whether include the commodities with no selected lagged returns or not, are both highly significant. For example, when we only include the commodity futures with selected lagged returns as predictors, the LASSO portfolio has an annualized mean return of 15.15%, which is more than eight times the mean return of the prevailing mean portfolio (1.78%). Coupled with a smaller standard deviation, the annualized Sharpe ratio of this LASSO portfolio is thus much higher than those of the two benchmark portfolios, 0.93 versus

[12] Downside risk is measured with the semi-standard deviation $DR = \sqrt{(\frac{1}{T})\sum_{t=1}^{T}\min(r_{p,t},0)^2}$, Sortino ratio is the mean excess returns of the portfolio divided by the downside risk.

0.10 (prevailing mean) and -0.21 (OLS). It also has much smaller downside risks than the two benchmarks. The performance of the LASSO portfolio when all the commodity futures are included (LASSO (All)), is very similar to the LASSO portfolio.

Next, we evaluate the risk-adjusted performance of the single-sort portfolios using a multi-factor model. The factors include Bakshi et al.'s (2019) three factors and Kang et al. (2020) hedging pressure factor. Bakshi et al. (2019) advocate three factors in commodity futures, they are the average factor, the basis factor, and the momentum factor. The average factor is the average returns of all the commodity futures, the basis factor is constructed based on the basis, measured by the difference in the logarithmic prices of the nearest and second-nearest contracts. The commodity futures is in contango (backwardation) when the basis is positive (negative). The basis factor is constructed by buying the five most backwardated futures and selling the five commodity futures that are in most contango. The momentum factor is constructed by buying the five commodity futures with the highest past 12-month cumulative returns and selling the five commodity futures with the lowest past 12-month cumulative returns. Bakshi et al. (2019) claim that the three factors can jointly explain the cross-section of commodity futures returns. We also include the hedging pressure factor. Basu and Miffre (2013) discover that hedging pressure, measured by the ratio of the commercial traders' net short position to open interest in that commodity, generates significant risk premium, which is consistent with Keynes (1930) and Hirshleifer's (1990) hedging pressure theories. Kang et al. (2020) posit that the traditional measure of hedging pressure consists of two parts: a short-term variation that provides liquidity for non-commercial traders, and a long-term variation that is mainly driven by commercial traders' hedging demand, and argue that only the latter part generates risk premium. They use the 52-week moving average of hedging pressure as the measure of the commercial traders' hedging demand.

We follow Kang et al. (2020) and construct the smoothed hedging pressure as the 12-month moving average of commercial net short position (commercial short minus commercial long positions) scaled by the open interest. Then we construct the hedging pressure factor by buying the five commodity futures with the highest last month's smoothed hedging pressure and selling the five commodity futures with the lowest last month's smoothed hedging pressure. [13]

As shown in Table 4, the benchmark portfolio constructed from the prevailing mean has an insignificant alpha, and it has large loadings on the average factor, hedging pressure factor, and momentum factor. The four factors can explain 35.28% of the variation of returns based on the adjusted R-squared. The OLS benchmark has an insignificant alpha and a small but negative adjusted R-squared. In contrast, the two portfolios based on LASSO forecasts have highly significant and positive alphas with small adjusted R-squared. The LASSO portfolios generate an annual alpha of 16.61% $(1.384\% \times 12 = 16.61\%)$, and 14.59% $(1.216\% \times 12 = 14.59\%)$, respectively, when we exclude or include commodity futures with no predictors. The large alphas generated by LASSO forecasts indicate that investors can have significant economic gains by utilizing the lagged returns when predicting the individual futures returns.

I.5.2 Timing strategy

In this subsection, we further examine the performance of the lead-lag relations based on a timing trading strategy. For every month in the out-of-sample period and for each commodity future, we establish a long position if its forecasted return is positive and a short position if its forecasted return is negative. We then form the equally-weighted portfolio of all the positions.[14]

[13] The risk-adjusted performance in Section I.5 and Section I.7 is robust to adding other factors such as value (Asness, Moskowitz and Pedersen, 2013), skewness (Fernandez-Perez, Frijns, Fuertes, and Miffre, 2018), and basis-momentum (Boons and Prado, 2019).

[14] It is equivalent to a strategy that longs commodity futures with positive forecasted returns and shorts commodity futures with negative forecasted returns.

Similarly, the forecasts are based on the two versions of LASSO regressions along with the two benchmarks, prevailing mean and OLS.

Table 5 reports the performance of the timing portfolios. Clearly, the two LASSO portfolios outperform the two benchmark portfolios, prevailing mean and OLS. The LASSO portfolio yields an average excess returns of 6.15% per year, a Sharpe ratio of 0.72, and a Sortino ratio of 1.16. The performance is not subsumed by the multi-factor model. After adjusted for risk using the four-factor model, it still has an annualized alpha of 7.26% and is statistically significant at 1% level. When we include all the commodity futures including those with no predictors, the performance of the LASSO portfolio (LASSO (All)) deteriorates to some extent, but it still generates an annual mean return of 3.53% and an annual Sharpe ratio of 0.53. In contrast, the prevailing mean portfolio generates an annual return of only 1.80%, the OLS portfolio generates an even smaller average return that is less than 1%. Neither of them is statistically significant. The two benchmarks also have insignificant abnormal alphas based on the four-factor model.

Figure 1 depicts the cumulative logarithmic returns of the single-sort and the timing portfolios based on the return forecasts. In line with Table 3 and Table 5, the portfolios based on OLS forecasts have the lowest cumulative returns during the whole out-of-sample period. The prevailing mean portfolios have larger cumulative returns than the OLS, but cannot compete with the portfolios based on LASSO forecasts. For the timing strategy, the two LASSO portfolios also outperform the benchmarks even though there is an initial underperformance relative to the prevailing mean benchmark.

Overall, we find that LASSO performs much better than the prevailing mean and OLS. The number of candidate predictors is 54, which is almost the same as the number of observations 60, thus OLS is vulnerable to overfitting. Prevailing mean only considers the historical average returns but ignores all the other information, including the futures' own lagged returns and the links among commodity futures, and thus its out-of-sample forecast is very weak, at least during the last decade. By contrast, LASSO selects sparse but economically important predictors from the lagged returns, thus incorporating important information in the lagged returns and avoiding overfitting.

I.5.3 Other benchmarks

Although our main benchmark portfolios are based on the prevailing mean and the OLS, we also test other benchmarks, including autoregressive models and other predictors that are commonly used in commodity futures literature. They are three autoregressive models, including using the lagged one-period returns (AR1), the lagged one-and two-period returns (AR2), and the first three periods of lags (AR3) as the predictors. The other predictors include the 12-month cumulative returns (momentum), the difference in the logarithmic prices of the nearest and second-nearest contracts (basis), both of the two predictors (basis and momentum), the 12-month moving average of commercial net short position (hedging pressure), and all the three predictors (basis, momentum, and hedging pressure). For each set of predictors, we run a 60-month rolling regression and calculate the one-step ahead out-of-sample return forecast. Then we build the single-sort and timing portfolios. The results are displayed in Table 6. We find that none of those benchmark models outperform LASSO forecasts, especially in the timing portfolio.

I.6 Tests of Financialization

In this section, we test our hypothesis that financialization causes the excess comovement among commodity futures in multiple ways, including separating the indexed commodity futures from the non-indexed ones and testing whether the trading of the broad basket commodity ETFs affects the lead-lag relations.

I.6.1 Indexed futures versus non-indexed futures

Following Da et al. (2020), we classify the commodity futures included in both Bloomberg Commodity Index (BCOM) and S&P Goldman Sachs Commodity Index (GSCI) as indexed futures, and those included neither in BCOM nor GSCI index as non-indexed futures. There are 16 indexed futures and 7 non-indexed futures in our sample.[15] We then conduct the out-of-sample analysis separately using the indexed futures and non-indexed futures, and report the results in Table 7 and Table 8, respectively. As shown in Table 7, when we use indexed-only futures to run the lead-lag predictive regressions, the LASSO portfolio generates economically and statistically significant out-of-sample returns in both the single-sort and timing strategies. However, when we use the non-indexed futures to run the lead-lag predictive regressions as shown in Table 8, the two LASSO portfolios no longer generate any significant out-of-sample returns. These results support our premise that the lead-lag relations are partially caused by index trading after the financialization period.

I.6.2 ETF inception

If index trading causes the excess comovement among commodity futures, then the lead-lag relations will be more significant after the inception of broad commodity futures ETFs (or ETNs). To test this premise, we select the following three ETFs: iPath® Bloomberg Commodity Index Total Return SM ETN (DJP), iPath S&P GSCI Total Return Index ETN (GSP), and iShares S&P GSCI Commodity-Indexed Trust (GSG), and create a binary variable that is equal to 1 when the commodity futures are indexed and when the date is after the inception of the three products

[15] The 16 indexed futures include coffee, copper, corn, cotton, crude oil, gasoline, gold, heating oil, Kansas wheat, lean hogs, live cattle, natural gas, silver, soybean, sugar, and wheat futures , the 7 non-indexed futures include lumber, milk, oats, orange juice, palladium, platinum, and rough rice futures.

(September 2006),[16] otherwise 0. We then add the dummy as well as its interaction with all the lagged returns as the additional predictors and run the OLS post-LASSO regression using the full sample. The results are exhibited in Table 9 for the indexed futures. Overall, at least one lagged commodity futures return is selected for 14 of the 16 indexed futures. In addition, 10 out of the 14 futures have interactions of ETF inception dummy with lagged returns as selected effects, and the hypothesis that the interactions are all equal to 0 is rejected for all the 10 futures. The results support our premise that ETF trading during the post-financialization period is an important cause of the excess comovement among commodity futures.

I.7 Robustness Check

We check the robustness of our results in several ways. First, we explore other LASSO models. Second, we adjust for seasonality. Third, we consider adding more lags in the predictive regressions. Finally, we explore other machine learning models, including regression trees and neural networks.

I.7.1 Other LASSO models

I.7.1.1 Adaptive LASSO

LASSO may select too many predictors unless certain conditions on the design matrix are satisfied. Zou (2006) develops a two-step procedure, called adaptive LASSO to solve this issue. Following the spirit of Zou (2006) and Freyberger et al. (2020), we first estimate LASSO to obtain the coefficients, then estimate a weighted LASSO, where the weights are based on the coefficients

[16] iPath® Bloomberg Commodity Index Total Return SM ETN (DJP) tracks the Bloomberg Commodity Index TR, iPath S&P GSCI Total Return Index ETN (GSP) and iShares S&P GSCI Commodity-Indexed Trust (GSG) tracks the S&P GSCI total returns. The creation dates for DJP and GSP are 6/6/2006, the creation date for GSG is 7/10/2006. We choose September 2006 as the threshold because of illiquid trading during the first several months. There are also several other ETFs/ETNs listed in London and we do not consider them currently.

from the first step. By assigning weights in the second step, some of the first-step LASSO coefficients become 0. Specifically, the objective function of the second step LASSO is:

$$\min_{a_i \in R, b_i \in R^n} \| y_i - a_i l_{(T_i)} - X b_i \|_2^2 + \lambda_i \left(\sum_{j=1}^{M} \mathrm{w}_{i,j} \, | b_{i,j} | \right) \tag{7.1}$$

Where $w_{i,j} = 1 / \left| \widehat{\beta}_{i,j} \right|^{v}$ and $\widehat{\beta}_{i,j}$ is the LASSO coefficients in the first step and $\boldsymbol{v} > \mathbf{0}$. We choose $\boldsymbol{v} = \mathbf{1}$.

I.7.1.2 Elastic net

When there are some highly correlated variables in the predictors, LASSO tends to select just one of them. Elastic net solves this problem by adding an l_2 penalty to LASSO. The objective function for elastic net is:

$$\min_{a_i \in R, b_i \in R^n} \sum_{i=1}^{T_i} (y_i - a_i l_{(T_i)} - X b_i)^2 + \lambda_i \left(\alpha \sum_{j=1}^{M} | b_{i,j} | + \frac{1-\alpha}{2} \sum_{j=1}^{M} | b_{i,j}^2 | \right) \tag{7.2}$$

Where α is a blending factor between 0 and 1. The penalty term is a convex combination of l_1 penalty (LASSO) and l_2 penalty (Ridge). We assign 0.5 for the blending parameter and use AICC to select the two penalty parameters.

I.7.1.3 Combination LASSO

Han, He, Rapach, and Zhou (2019) propose a combination LASSO (C-LASSO) approach to improve the out-of-sample performance of LASSO, which combines univariate forecasts from each candidate predictor. In this paper, we use a 60-month rolling window to estimate combination LASSO. For each commodity futures, we first use 30 months to estimate univariate regression from regressing its returns on each lagged returns to obtain the coefficient estimates, then we use the coefficients to obtain the OLS forecasts of each lagged returns for the next 31 months. We use month 31 to month 60's OLS forecasts to estimate LASSO. The return forecast for month 61 is the average of the OLS forecasts on month 61 selected by LASSO.

I.7.2 Adjusting for seasonality

Commodity futures returns may have seasonality due to the seasonality of the demand and supply of the underlying commodities (Bianchi et al., 2016; Fernandez-Perez et al., 2018). To adjust for seasonality, we follow Fernandez-Perez et al. (2018) and add 11 month dummies to the original predictors. Now the number of predictors is 65 ($11 + 2 \times 27 = 65$), which is larger than the estimation window 60 months. OLS is unable to estimate such models but LASSO can select a subset of predictors even if there are more candidate predictors than data points used to fit the model.

I.7.3 Adding more lags

We include two lags as the candidate predictors in the main analysis, but it is possible that the further lags can affect the returns of commodity futures. So we include up to three lags. Now the number of predictors is 81 ($27 \times 3 = 81$).

Table 10 reports the out-of-sample performance of the single sort portfolio and the timing portfolio for each of the three models. The results in Table 10 are comparable to those presented in Table 3-Table 5, and sometimes are even stronger than the original results (e.g., the seasonality results shown in Panel D1 and D2 of Table 10), indicating that our results are robust.

I.7.4 Regression trees and neural networks

So far we use LASSO models to analyze the lead-lag relations, and these LASSO models assume linearity of the lead-lag relations. In this section, we examine the out-of-sample performance of the lagged return based on more complex models such as regression trees and neural networks. These models take account of nonlinearity and interactions between the independent variables. We use two tree-based models, including gradient boosting (Friedman, 2001) and random forest (Breiman, 2001), both with 500 trees. For the neural network models, we only consider one hidden layer since the estimation window is only 60 months and neural networks with a single layer usually perform well in small dataset. Adding more layers may make the neural network more opaque and complicated without improving the performance of prediction.

Table 11 shows the results of the two tree-based models. The single-sort portfolios perform well. The gradient boosting (random forest) model has an annualized return of 12.54% (13.38%), which is similar to the performance of the baseline LASSO model (15.15%). The timing portfolio constructed by the two tree-based models perform poorly with insignificant mean return and multi-factor alpha.

Table 12 shows the results of single-layer networks with different number of neurons. As shown in Panel A, the single-sort portfolios perform poorly no matter how many neurons are in the hidden layer. which may be due to insufficient amount of data to train more complicated models. The timing portfolios of the neuron network models also perform poorly regardless of the number of neurons.

Overall, tree-based models and neuron networks perform worse than LASSO based models, indicating more complexed machine learning models may not be applicable to our estimation model setting in which the estimation window is relatively small.[17]

I.8 Conclusion

This paper exploits the serial dependence of the commodity futures returns via machine learning tools to analyze return predictability in commodity futures markets. The candidate predictors are the first and second lagged returns of all the commodity futures. Because the number of candidate regressors is large relative to the number of observations used to fit the model, we apply LASSO to select the predictors.

While the full-sample result is interesting that the selected predictors are sparse and sometimes unexpected with no apparent economic links, the out-of-sample results suggest that the predictability of futures returns has great economic significance. We analyze two different kinds of long-short portfolios, one is a zero-cost single-sort portfolio that buys (sells) the commodity futures with the five highest (lowest) return forecasts, the other is a timing strategy that buys (sells) the commodity futures whenever the forecasted returns are positive (negative). We find that the two strategies earn economically and statistically significant average returns with low volatilities and downside risks. The superior performance survives the risk adjustment using the multi-factor asset pricing models in the commodity futures markets.

We further investigate whether financialization plays an important role in the predictability of futures returns. When we separate the indexed futures from the non-indexed futures, we find

[17] Gu et al (2019) find that tree-based models and neural network perform well in predicting stock markets. They use expanding window with minimum estimation window of 19 years, and the models are performed in a cross-sectional setting, thus the sample size is much larger than the number of anomalies. However, our LASSO regressions are time-series regressions and we do one-month ahead forecast.

that the LASSO strategy only works in indexed futures, suggesting that index trading is an important cause of the excess comovement among commodity futures. Moreover, the lead-lag relations are stronger after the advent of ETFs or ETNs that track the broad futures indices such as GSCI and BCOM indices. The above results are robust to several alternative approaches such as adaptive LASSO, elastic net and adjusting for seasonality.

Overall, our results suggest that both autocorrelations and cross-serial correlations contain valuable information to predict the futures returns and that machine learning is a useful and effective tool to increase the out-of-sample predictability.

CHAPTER II A TREND FACTOR IN COMMODITY FUTURES MARKETS

II.1 Introduction

Trend-following strategies have been widely used by commodity trading advisors and have received extensive attention from the academics. Momentum is one of the most studied trend-following strategies in the literature (e.g., Erb and Harvey, 2006; Miffre and Rallis, 2007; Shen, Szakmary, and Sharma, 2007; Moskowitz, Ooi and Pedersen, 2012; Hurst, Ooi and Pedersen, 2017; Huang, Li, Wang, and Zhou, 2020), which utilizes intermediate-term trend signals (usually 6 months or 12 months). Han, Hu, and Yang (2016) extend the trend studies to short horizon. They find that 5-day moving average signals can outperform the buy-and-hold benchmark. Long-term trend signals are not widely studied because commodity futures market is found with little evidence of long-term reversal (Bianchi, Drew, and Fan, 2016). However, a combination of short- and long-term trend signals can be profitable. Narayan, Ahmed, and Narayan (2015) find that multiple trading strategies based on the difference between the short- and long-term moving averages perform well. Bianchi et al. (2016) find that a double-sort strategy based on momentum and long-term reversal generates significant returns. Recently researchers also combine the trend signals with other characteristics of commodity futures such as the term structure and find superior out-of-sample performance (e.g., Boons and Prado, 2019; Paschke, Prokopczuk, and Simen, 2020).

This paper studies the profitability of a trend factor that incorporates short-term, intermediate-term, and long-term trend signals. Our methodology closely follows Han, Zhu, and Zhou (2016). The trend signals are calculated from the moving averages of past settlement prices from 3 days to up to 600 days. Then we obtain the expected trend returns by cross-sectional regressions. We construct the trend factor by buying the futures with the highest ranked forecasted returns and shorting those with the lowest ranked forecasted returns, thus our test is a cross-section test of the predictability rather than a time-series test.[18] We evaluate the performance of the trend factor by comparing it with the momentum benchmark and run the 2-step regressions to estimate the risk premium of the trend factor. We also use multivariate regressions, including Fama-Macbeth regression and pooled OLS regression to test the predictive power of the expected trend returns.

The annualized mean return of the trend factor is 13.48% and is statistically significant during our sample period 2004-2019. In contrast, the annualized mean of the momentum factor is 2.06% and is insignificant.[19] Then we test whether the trend factor is a priced factor. We find that the return of the trend factor cannot be subsumed by multi-factor models. The annualized alpha of the trend factor with respect to the benchmark multi-factor models are always economically and statistically significant. For example, the annual alpha with respect to Sakkas and Tessaromatis (2020) six-factor model is 13.44% ($1.12\% \times 12 = 13.44$). The GRS tests provide additional supports in a joint-regression setting, with F statistics rejecting the null hypothesis that the quintile trend portfolios are jointly equal to 0. We also run cross-sectional multivariate regressions to test the predictive power of the expected trend returns. Next, we run the 2-step cross-sectional regression results to test the risk premium of the trend factor, and the result indicates that the trend

[18] Time-series based trading strategy involves taking positions based on the security's own returns. In contrast, the positions in cross-sectional based trading strategy are based on the relative performance of securities. See Goyal and Jegadeesh (2018) for a detailed examination of the difference between time-series and cross-sectional tests of predictability. Miffre (2016) also has an excellent summary of the trend literature categorized by the time-series and cross-sectional tests.

[19] If we change the starting year to 1979 (which is also the starting time period of Miffre and Rallis, 2007) or 1983 (which it the same as the starting time period of Narayan et al., 2015), the momentum factor will be statistically significant. So the performance of the momentum factor seems to be weakened substantially during the more recent time period. The summary statistics of factors studied in this paper based on extended sample period is presented in APPENDIX B.

factor is priced cross-sectionally. Overall, the results show that the expected trend returns have predictive power.

Last but not least, we examine the determminants of the profitability of the trend factor. The candidate explanotary variables include multiple marcoeconomic variables, stock market factors, market liquidty, and investor sentiment. We find that the trend factor return is positively related to TED spread, indicating that commodity futures can be attractive alternative assets when the funding liquidity in the credit market is lower.

The main contribution of this study is that we identify a new profitable trend strategy that outperforms the well-studied momentum in commodity futures markets. We are the first to apply Han et. al.'s (2016) method to commodity futures markets, which jointly considers the short-, intermediate-, and long-term trend signals. Second, we identify a new pricing factor that cannot be explained by existing factors. Third, this paper identifies a link between funding liquidity and the trend factor profitability.

II.2 Literature review with theoretical support

In this section, we discuss literature regarding time-series trend and cross-sectional trend, and the theories explaining the predictability of trends in commodity futures markets.

One strand of literature focuses on time-series trend, which is based on time-series regressions and examine the instrument's own past trend. Time-series based trading strategies involve taking positions based on the instrument's own return. A typical time-series strategy is to buy securities with positive trend signals and sell those with negative signals. In contrast, the positions in cross-sectional trading strategy are based on the relative performance of securities. A typical cross-section strategy is to buy the securities with the highest ranks of the trend signals and sell the securities with the lowest ranks.

II.2.1 Time series trend

Moskowitz et al. (2012) use 58 futures and forwards contract to study whether an instrument's past returns can help predict its own future returns. They find that a security's own past one to 12-month returns can predict future returns based on pooled OLS regression, when the holding periods are less or equal to 12 months. They also build a trading strategy that shorts the contracts with negative time-series momentum signals and longs the contracts with positive time series momentum. This strategy has significant alphas over factor models. Hurst et al. (2015) extend the sample period to over one century, which is from 1880 to 2016. The sample period includes the great depression, multiple war periods, and other economic booms and bust periods. They find that time-series momentum has been profitable through the whole sample period, confirming that Moskowitz et al. (2012) is not purely a statistical artifact.[20] However, these studies use pooled OLS regression to identify the predictability of time series momentum without controlling the fixed effects of the instruments, which leads to upward biased slope coefficient estimates if the assets have different means (Hjalmarsson, 2010). Huang et al. (2020) use bootstrap simulations to identify the critical value of t-statistics that should have been used to evaluate the slope coefficient in pooled OLS regression, and they find that Moskowitz et al.'s (2012) results become much weaker. They also compare the time-series momentum strategy with a time-series mean strategy that does not require any predictability and find that the two strategies are

[20] Also see Kim and Wald (2016); Georgopoulou and Wang (2017); Lim, Wang, and Yao, (2018); Pitkäjärvi, Suominen, and Vaittinen (2020); among others.

statistically indifferent. Nevertheless, Moskowitz et al.'s (2012) time-series momentum is implementable from an investor's perspective.

Han, Hu, and Yang (2016) study the predictability of the short-term trend. They find that a moving-average timing strategy that uses the 5-day moving average price signals can outperform the buy-and-hold benchmark. Their results are robust to alternative moving average lengths and transaction cost.

Paschke et al. (2020) introduce curve momentum. They use the excess returns of the past 12 months for the nearby and the second-nearby contracts to measure the trend signals, and they buy(sell) the contracts with high (low) trend signals and construct equal-weighted excess return for each month. Thus they build a time-series strategy in commodity futures markets. They find that their strategy cannot be explained by risk factors and it becomes stronger after the passage of the Commodity Futures Modernization Act in late 2000, suggesting that speculation explains the performance of curve momentum.

II.2.2 Cross-sectional trend

Erb and Harvey (2006) find that momentum strategy based on past 12-month cumulative returns generate significant returns. The sample period is from December 1982 to May 2004. Shen et al. (2007) find that momentum strategy is profitable in commodity futures market for a ranking and holding periods up to 9 months. Miffre and Rallis (2007) examine the momentum strategy with different ranking and holding periods and identify 13 profitable momentum strategies when the ranking and holding periods are less or equal to 12 months. They also find that long-term contrarian strategies do not work in commodity futures market. Bianchi et al. (2016) find that double sort strategy of momentum and long-term contrarians generate significant returns and outperform single-sort momentum strategy. Boons and Prado (2019) introduce a basis-momentum strategy, which is the difference between the 12-month cumulative returns in the first and second-nearby futures. Then they build single-sort portfolios based on the rank of the basis-momentum. They find that the basis-momentum can predict the nearby and the second-nearby futures returns, and it outperforms both basis and momentum.

II.2.3 Explanations on trend-based strategies

II.2.3.1 Behavioral models

Daniel, Hirshleifer, and Subrahmanyam (1998) develop a model where investors have biased self-attribution and rely more on their private signals. Their model predicts opposite-direction price trends in the long run and same-direction price trends in the short run. Hong and Stein's (1999) model features two types of investors, namely, "newswatchers" who rely on their private signals to forecast future fundamentals and momentum traders whose forecasts are conditional on past prices. They find that momentum traders can arbitrage away the newswatchers' underreaction by chasing trends. Grinblatt and Han (2005) find that prospect theory and mental accounting can explain momentum profits.

2.3.2 Rational models

Brown and Jennings (1989) develop a two-period equilibrium model. In their model, the past prices are a function of exogenous information (such as the asset supplies and payoff). They find that under mild assumptions of parameter restrictions, technical analysis always has value in the myopic-investor economy. Grundy and Kim (2002) develop a multi-period model with heterogeneous information economy, in which each rational investor has his own heterogenous private signals. They find that rational traders can use past price information to revise their expectation on future dividend. Johnson's (2002) model find that dividend growth rate shocks can cause price momentum in the stock market.[21] Zhu and Zhou (2009) develop a continuous-time theoretical model to explicitly model the predictive power of moving averages. In their model, an investor allocates her wealth between a riskless asset and a stock, and the trading rule of the stock is to buy the stock when its current price is above its moving average price during a specific window otherwise do nothing. They find that a generalized moving average rule, which is a mix of the traditional mean-variance solution and the moving-average strategy, outperforms the optimal strategies that are based on reasonable but uninformative prior or derived from the wrong models. Overall, their theoretical model highlights the informativeness of moving averages when there is uncertainty about predictability.

The performance of the trend strategies in commodity futures markets can be explained by either behavioral or rational theories. First, starting from 2004, financial institutions and individuals have gained access to commodity futures, who use commodity futures as investment assets or speculation. Therefore, behavioral models may explain the trend strategy. Second, based on the rational models discussed in the above section, trend signals can predict future returns under mild assumptions such as when there is uncertainty about predictability. There are debates about the risk premiums in commodity futures. For instance, the studies (e.g., Szymanowska, De Roon, Nijman, and Goorbergh, 2014; Bakshi et al., 2019) that find significant cross-sectional pricing of some factors usually use commodity futures portfolios as testing assets to estimate risk premia. Daskalaki, Kostakis, and Skiadopoulos (2014) use individual futures to test the risk premiums and find no evidence of any priced factors. Therefore, analogous to the model prediction of Zhu and

[21] The return of commodity futures is rarely decomposed to cash flow shocks and dividend yield shocks. The "fundamentals" in commodity futures markets are more related to macroeconomic conditions.

Zhou (2009) for stock market, using technical analysis in commodity futures markets may add wealth to investors.

Han et al. (2016) also develop a parsimonious model to justify the usefulness of moving averages. Their empirical results strongly support their theoretical prediction. We follow their methodology to construct the expected trend return and apply it to commodity futures markets. We find that their trend strategy works well in commodity futures markets.

II.3 Data

We collect the settlement price, the aggregated open interest, commercial traders' long and short positions of 27 commodity futures that are traded actively in the US. The data are collected from Bloomberg. The 27 commodity futures cover five main sectors, namely, grains, softs, energy, livestock, and metal. There are 8 grains futures, 7 softs futures, 3 livestock futures, 4 energy futures, and 5 metal futures in the sample. The sample period is January 2004-December 2019.

The futures contracts that are closed to expiration dates are rarely traded due to the possibility of physical delivery, so we roll-over the contracts 15 days before the expiration dates, rather than during the expiration day. That is, the nearby contract is replaced by the second nearby contract 15 days before the expiration dates. Due to contango or backwardation, the nearby and the next-nearby contracts always have different settlement prices on the roll-over day and thus will cause jumps in futures prices. Following Han et al. (2015) we adjust the future prices by the ratio of the second nearby to the nearby contracts on the roll-over day.[22] Now we have a continuous time-series of settlement prices for each commodity futures. Then we use the new price series to

[22] We can obtain such adjusted price series from Bloomberg by using adjusted ticker to download the settlement price. For instance, the adjusted ticker of the soybean meal futures is BO1 R:15_0_R Comdty, in which the first R means expiration, the last R means ratio, 15 means 15 days before expiration.

calculate moving averages and obtain the monthly returns as the percentage change of the month-end prices.[23]. APPENDIX C summarizes the excess return based on the current rollover method.

II.4 Methodology

To construct the trend factor, following Han et al. (2016), we first calculate the moving average settlement prices of each month. The moving average of month t of lag L is defined as

$$A_{jt,L} = \frac{P_{j,d-L+1}^{t} + P_{j,d-L+2}^{t} + \cdots + P_{j,d-1}^{t} + P_{j,d}^{t}}{L}, \tag{4.1}$$

Where $P_{j,d}^{t}$ is the settlement price for commodity futures j on the last trading day d of month t, and L is the total number of lags. $A_{jt,L}$ thus is the average price of the past $L-1$ days and day d. Then, we normalize $A_{jt,L}$by the month-end settlement price,

$$\tilde{A}_{jt,L} = \frac{A_{jt,L}}{P_{j,d}^{t}}. \tag{4.2}$$

The reason for normalization is to make the MA series stationary and comparable across commodity futures. Then we estimate the expected returns with two steps. First, we run a cross-section regression of commodity futures returns on the normalized moving average signals to obtain the coefficients on the signals,

$$R_{j,t} = \beta_{0,t} + \sum_{i} \beta_{i,t} \tilde{A}_{jt-1,L_i} + \epsilon_{j,t}, \quad j = 1, \ldots, n, \tag{4.3}$$

[23] We also use the non-adjusted prices that do not cross contracts to calculate the monthly returns and use ratio-adjusted prices to construct moving averages. Our results are robust to this specification. See the robust test section (Section III.5) for a detailed description of the return calculation.

Where $R_{j,t}$ is the excess return on commodity futures j in month t, $\tilde{A}_{jt-1,L_i}$ is the trend signal at the end of month t-1 with lag L on commodity futures j at the end of month $t-1$, $\beta_{i,t}$ is the slope coefficient on the trend signal, $\beta_{0,t}$ is the intercept, n is the number of commodity futures in each month. We consider lag lengths 3, 5, 10, 20, 50, 100, 200, 400, and 600 days. These signals include the short-run, intermediate-run, and long-run signals.

Then we obtain the expected return for month t based on the following equation

$$E_t\left[R_{j,t+1}\right] = \sum_i E_t\left[\beta_{i,t+1}\right]\tilde{A}_{jt-1,L_i}, \tag{4.4}$$

Where $E_t\left[R_{j,t+1}\right]$ is the forecasted returns for month $t-1$, $\sum_i E_t[\beta_{i,t+1}]$ is the expected coefficient signal of lag L_i, which is given by

$$E_t\left[\beta_{i,t+1}\right] = \frac{1}{60}\sum_{m=1}^{60}\beta_{i,t+1-m}, \tag{4.5}$$

We then form the trend factor based on the expected trend return. First, we sort all the commodity futures based on the expected trend returns. Then we construct two equal-weighted portfolios $High$ and Low. The $High$ (Low) portfolio consists of 5 commodity futures with the highest (lowest) expected trend returns. The trend factor is obtained by buying in $High$ and selling Low.

II.5 Results

II.5.1 Summary statistics of the factors

First, we compare the trend factor with other commonly studied factors in commodity futures markets, including the momentum factor (Bakshi et al., 2019), hedging pressure factor

(Basu and Miffre, 2013; Kang, Rouwenhorst, and Tang, 2020), basis factor (Szymanowska et al., 2016), the average factor, the basis-momentum factor (Boons and Prado, 2019), and the value factor (Asness, Moskowitz, and Pedersen, 2013). All the factors, except for the average factor, are based on the rank of the commodity futures' own characteristics. For example, the momentum factor is constructed by going long the 5 commodity futures with the largest past 12-month cumulative returns and selling the 5 commodity futures with the lowest past 12-month cumulative returns (Bianchi et al., 2016). The hedging pressure factor is based on the rank of the 12-month moving average of commercial net short position (commercial short minus commercial long positions) scaled by the open interest (Kang et al., 2020). [24] The basis factor is based on the basis of the commodity futures, which is measured as the logarithm of the ratio of prices of the nearby to the second-nearby contracts. The commodity futures are in contango (backwardation) when the basis is positive (negative). [25] The basis-momentum factor is constructed by going long (short) the five commodity futures with the largest (lowest) basis-momentum. The value factor is constructed by going long (short) the five commodity futures with the largest (lowest) ratio of the average futures prices 4.5 to 5.5 years ago to past month's futures price. The average factor is the equal-weighted return of all the commodity futures, which is equivalent to the market portfolio in the stock markets. Bakshi et al. (2019) find that the average, momentum, and basis factors are priced in commodity futures markets. Boons and Prado (2019) find that basis-momentum factor and the average factor can explain a large variation of the cross-sectional returns. Sakkas and Tessaromatis (2020) find that a combination of the six factors outperform models constructed with other factors.

[24] Notice that Basu and Miffre (2013) use the percentage of ***long*** positions to measure the hedging pressure, while Kang et al. (2020) define the net short (***short minus long)*** position as hedging pressure. So Basu and Miffre's (2002) factor construction is to buy low sell high, Kang et al.'s (2020) factor construction (and thus ours) is to buy high sell low.

[25] The basis is calculated with the unadjusted futures prices, rather than ratio-adjusted prices used to calculate returns.

Table 13 shows the summary statistics of all the seven factors mentioned above. The average annualized return of the trend factor from January 2004 to December 2019 is 13.48%, which is more than five times the mean of the momentum factor. The mean of the trend factor is statistically significant while the mean of the momentum factor is not. The two factors have similar standard deviations, thus the trend factor's Sharpe ratio is more than five times of the momentum factor's. The hedging pressure factor has an annualized mean of 9.01% and is statistically significant. The basis and average factors are not statistically different from 0. The insignificant mean of the average factor indicates that the commodity futures markets during the financialization period perform poorly, which is consistent with the disappointing performance of the long-only broad commodity futures indices such as Bloomberg Commodity Index (BCOM) and S&P Goldman Sachs Commodity Index (GSCI).[26]

We then check the performance of the trend factor in good times versus bad times. We report the summary statistics separately for the recession and expansion periods in Table 14. During our sample period 2004-2019, the only recession period is the financial crisis. As shown in Panel A, the annualized mean of the trend factor is 35.05%, which is much larger than the mean 11.25% during the expansion period shown in Panel B. The trend factor has a larger standard deviation in the financial crisis period than in the expansion period, making the Sharpe ratios in financial crisis almost three times as that in expansion period. In contrast, the momentum factor has insignificant mean during the two economic conditions, and it performs much worse during the financial crisis period. It has a much smaller mean and is more volatile during the financial

[26] Based on the data from the Bloomberg terminal, from January 2004 to December 2019, the average annual return of the S&P GSCI excess return index is -2.24%, the average annual return of the BCOM excess return index is –1.92%.

crisis period than the expansion period. Both the mean and the Sharpe ratio during the financial crisis are negative. Moreover, none of the other three factors have significant mean when we separate the two economic conditions.

II.5.2 Tail risk

Panel A of Table 15 reports the measurements of tail risk, including the maximum drawdown (MDD), Calmar ratio, and frequency of large losses. The maximum drawdown measures the largest decline from a peak to a trough of a portfolio. The Calmar ratio is the ratio of the average return to the absolute value of the maximum drawdown. The two measurements are common indicators of the downside risk of an investment. A larger (smaller) magnitude of the maximum drawndown (Calmar ratio) indicates a larger downside risk. The maximum drawdon of the trend factor is only around 2/3 of the momentum factor. The Calmar ratio of the trend factor is ten times of the momentum factor (31.87% vs 3.26%). Furthermore, there are 10 (0) months when the trend factor returns are smaller than -10% (-15%), while there are 13 (1) months when the monthly returns of the momentum factor are smaller than -10% (-15%), indicating that the momentum factor has more extreme values than the trend factor. Overall, the above results indicate that the trend factor has smaller tail risk than the momentum factor.

II.5.3 Further comparison of the trend factor with the momentum factor

The correlation matrix is shown in Panel B of Table 15. The correlation between the trend and the momentum factor is 0.26. The large correlation is expected because both of them capture the trend signals of the past prices and returns. Table 16 further reports the summary statistics of the two factors, including the long leg and short legs of them. As shown in Panel A, during the whole sample period 2004-2019, the correlation of the long (short) legs between the two factors is

0.65 (0.63). The large correlations indicate that trend and momentum share some common information. However, the trend factor captures the past signals better than the momentum factor. It has a much larger mean than the momentum factor. In the long leg, the mean return of the trend factor is more than doubled the momentum factor, and the mean of the trend factor is much smaller than that of the momentum at the short leg. The mean of the two factors is statistically different for the short leg and the spreading (long-short) portfolio. Panel B shows the comparison of the two factors during the financial crisis period. The long leg of the trend factor has an annualized mean of 11.98%, and the long leg of the momentum factor has an annualized mean of -25.26%. The mean difference is statistically different from 0. Panel C shows the results during the expansion period. Similar to the whole sample and the financial crisis period, the trend factor always has a larger (smaller) mean than the momentum factor for the long (short) leg. Moreover, the standard deviations of the two factors (long, short, and spreading) are very similar, although the trend factor always has a smaller standard deviation than momentum.

II.5.4 Time-series tests

In this section, we examine whether multi-factor models can subsume the performance of the trend factor. The benchmark models include Boons and Prado (2019) two-factor model (basis-momentum and average), Bakshi et al., (2019) three-factor (momentum, basis, and average), Sakkas and Tessaromatis (2020) six-factor (momentum, basis, average, hedging pressure, basis-momentum, and value). The formation of these factors is explained in Section II.4.1. Table 17 reports the alphas and risk loadings of the short leg, long leg, and the spreading portfolios. The trend portfolios have large loadings on the momentum portfolios when momentum is included as a benchmark factor. For instance, in Panel B when the benchmark factor model is Bakshi et al. (2019), the loading of the Low (High) portfolio on the momentum factor is -0.21 (0.09), and the loading of the spreading portfolio (trend factor) on the momentum factor is 0.31. This is because both trend and momentum utilize the information on historical prices. However, none of the three factor models subsume the trend portfolios' returns. The Low, High, and the spreading portfolios all have significant alphas. The commodity futures with low expected trend returns (Low) have negative alphas, while the commodity futures with high expected returns (High) have a positive alpha. For example, the Low (High) portfolio has a monthly alpha of (0.09) with respect to Boona and Prado (2019) two-factor model, and the trend factor has a monthly alpha of 1.12%.

Next, we use five quintile trend portfolios as the test assets to do GRS tests. As shown in Table 18, the GRS F statistics can always reject the null hypothesis of the GRS test that the quintile trend portfolios jointly equals to zero. Overall, the above results indicate that the profitability of the trend factor cannot be explained by existing factor models.

II.5.5 Multivariate tests

Although single-sort can identify the pattern of the relation between the sorted variable and returns, it is difficult to control for many variables. Moreover, since the trend factor is constructed based on the highest and lowest ranks of the expected trend returns, it ignores the information of the medium ranked commodity futures. In this section, we use Fama-Macbeth regression and pooled OLS regression to test the predictability of the expected trend return. The independent variables include the expected trend returns (ER_{trd}^{12}), the cumulative 12-month returns ($R_{-1,-12}$), the logarithm of the ratio of prices of the nearby to the second-nearby contracts ($lnyt$), the 12-month moving average of commercial net short position (HP_{it}), basis-momentum (BASIS-MOM), and value (Value).

To estimate the Fama-Macbeth coefficients, first, at the end of each month, we regress the excess returns on the independent variables to obtain the loadings on these variables, then we calculate the time-series averages of the loadings. The t-statistics are calculated from the Newey-west standard errors with automatic lags. Since we take the average of the coefficients in the second stage, it eliminates any effects coming from time-variate variables such macroeconomic variables. Panel A of Table 19 reports the results. The coefficients on the expected trend return (ER_{trd}^{12}) are always positive and statistically significant (tstats larger than 3) in models (1) to (4). In contrast, the coefficients on momentum ($R_{-1,-12}$) are insignificant when it is added as a control variable in models (3) and (4), indicating that trend has more predictive power than momentum in a multivariate regression setting.

Although Fama-Macbeth regression accounts for time-variate effects, it does not control for the different means of each commodity futures. So we use pooled OLS regression with commodity futures fixed effects along with time fixed effects to reestimate the multivariate model mentioned above. The results are shown in Panel B of Table 19. The coefficients on ER_{trd}^{12} remains positive and statistically significant in all the four models. In contrast, the effect of hedging pressure is subsumed by the fixed effects, and the signs of the coefficients on momentum become either significant with the wrong sign (model 3) or insignificant (model 4). Overall, Table 19 shows that trend signals can predict returns in a multivariate regression setting.

II.5.6 Risk premium on the trend factor

Bakshi et al. (2019) use the individual commodity futures to build portfolios and use the portfolios to estimate both the beta and the risk premiums of the factors. Both the portfolios and the factors are created from the rank of the same set of variables.[27] Daskalaki et al. (2014) criticize that this method incurs tautology and risk premiums are always found using this method. When they use individual futures to test the risk premiums, none of the existing factors generate any risk premiums. However, the beta estimation of the individual commodity futures can be noisy and imprecise. To reduce the estimation error of the betas, we follow Fama and French (1993) to use the portfolios as the tested assets to estimate beta, then use the individual commodity futures to estimate the risk premiums of the factors. Specifically, first, every month we construct 9 equally weighted single-sort portfolios based on the expected trend returns, then we use the 9 portfolios as assets to estimate betas. Betas are obtained by regressing the portfolio returns on the five factors (trend, momentum, basis, hedging pressure, average). Then we regress the returns of the 27 individual commodity futures on the betas to estimate the risk premiums, then we average the risk premiums across months. We also use Shanken's (1992) method to adjust the standard errors of the risk premiums.

Panel A of Table 20 shows the results when betas are estimated using the whole sample period (so there's only one beta estimation for each commodity futures), Panel B shows the results when betas are estimated based on a constant window of 60-month. The risk premiums of the trend factor are alwas significant in the four different model specifications when using constant beta. When we use rolling windows to estimate betas, the trend factor is priced in three out of the four model settings. These results show that the trend factor is priced cross-sectionally.

[27] For instance, they sort the commodity futures based on the last 12-month cumulative returns to five quintiles and use the equal-weighted returns of the five momentum portfolio as the tested assets (five momentum portfolios), use the return difference between the 5 futures with highest last 12-month cumulative returns and the 5 futures with the lowest 12-month cumulative returns to construct the momentum factor.

II.5.7 What explains the profitability of the trend factor?

In this section, we explore the determinants of the trend factor. The explanatory variables include 3 macroeconomic variables, 2 variables related to liquidity, 6 stock market factors, and 1 sentiment variable. Following Paschke et al. (2020), the 3 macroeconomic variables include monthly growth rate of the industrial production, default spread (Moody's seasoned BAA yield − Moody's seasoned AAA corporate bond yield), and term spread (10-Year Treasury note yield rate −3-Month T-bill yield rate). The 2 variables related to liquidity include TED spread, which is 3-Month LIBOR less the 3-Month T-bill rate, and the innovation to the market liquidity of Pástor and Stambaugh (2003). The stock market factors include the Fama-French (2015) five factors and the momentum factor. These variables test rational asset pricing theories. The last variable is Baker and Wurgler's (2006) investor sentiment. We then run contemporaneous regression by regressing the trend factor on these variables. The results are illustrated in Table 21. The coefficients on TED spread is statistically significant and positive in the univariate regression or the multivariate regression when all the rational variables are included. The coefficient on investor sentiment is insignificant. These results seem to indicate that trend factor can be explained by TED spread. When TED spread is larger, there is less funding liquidity in the credit, however, trend strategy in commodity futures markets performs better, indicating that commodity futures can be attractive alternative assets when the funding liquidity is low.

II.6 Robust test

We conduct robust tests in multiple ways, including using a different roll-over method and use an alternative way to calculate the excess returns. We report the comparison of the trend and momentum factor (short; long; spreading) and the annualized alpha of the trend factor with respect to Sakkas and Tessaromatis (2020) six-factor.

II.6.1 Alternative roll-over method

First, we roll-over the contracts with active futures.[28] The results are shown in Table 22.

II.6.2 Using the original settlement prices to calculate returns

Next, we calculate the excess returns of the futures without crossing the contracts, thus we need to use the original settlement prices to construct the returns. The roll-over date is the same as the main analysis, i.e., 15 days before expiration. The daily excess returns are calculated as follows:

$$R_{i,d+1}^{(1)} = \begin{cases} \dfrac{F_{i,d+1}^{(1)}}{F_{i,d}^{(1)}} - 1, \text{if there is no rollover at the end of day d} \\ \dfrac{F_{i,d+1}^{(1)}}{F_{i,d}^{(2)}} - 1, \text{otherwise} \end{cases} \tag{6.1}$$

Where $F_{i,d+1}^{(j)}$ is the settlement price of the j_{th} nearby futures contract (roll-over 15 days before maturity) on day $d+1$, $F_{i,d}^{(j)}$ is the settlement price on day d. Then we compound the above daily excess returns to monthly excess returns. The results are displayed in Table 23.

As shown in Table 22 and Table 23, the results are very similar to the main findings in Table 14 and Table 17, i.e, the trend factor always performs better than the momentum factor, both during the full sample period and during economic recession and expansion. Moreover, the abnormal alpha of the trend factor (relative to Sakkas and Tessaromatis (2020) six-factor) are always statistically significant and economically large. Therefore, it is unlikely the trend factor suffers from statistical artifact.

[28] For instance, the adjusted ticker of the soybean meal futures is BO1 A:00_0_R Comdty.

II.7 Conclusion

In this paper, we construct a trend factor based on past returns and past settlement prices in commodity futures markets. It outperforms the momentum benchmark significantly. During our sample period 2004-2019, the trend factor generates statistically and economically large returns while the average return of the momentum factor is insignificant. The trend factor also has smaller downside risk than the momentum factor. The returns of the trend factor cannot be subsumed by existing multi-factor models. The trend factor also generates a positive risk premium cross-sectionally. Moreover, the trend factor can be explained by funding liquidity measured by TED spread. Overall, our results indicate that the past prices contain important information on the expected returns in commodity futures markets.

CHAPTER III INDUSTRY TOURNAMENT INCENTIVES AND CORPORATE INNOVATION STRATEGIES

III.1 Introduction

This paper studies how ITIs affect corporate innovation strategies. Product innovation is a major business activity for a firm. ITIs can affect product innovation through two channels. First, product innovation can differentiate a firm from the rivals in its market and is likely to increase the performance and the value of a firm. Therefore, CEOs are likely to engage in product innovation activities that have the potential to generate profitable outcomes and signalize their abilities. Both Kale, Reis, and Venkateswaran (2009) and Coles et al. (2018) find that the promotion-based tournament incentives among managers can increase firm performance. Second, product innovation is highly uncertain and risky. ITIs can provide convex payoffs because the job market tournament winner earns the pay gap between her original compensation and the compensation offered by the top firm as the tournament prize, while others receive nothing. This "winner-takes-all" payoff structure is similar to stock options and has been shown to increase firm riskiness (Coles, Daniel, and Naveen, 2006). Therefore, the option-like payoff of the tournament prize provided by the top firm in the industry can motivate CEOs to bear the excessive risk and undertake risky product innovation activities.

Product innovations could arise from patent-based technological innovation and/or "routine" product development. Technological innovations through patents act as long-term innovation activities as they require a long time, substantial investments, and managerial effort (Aghion and Tirole, 1994; Manso, 2011). Thus, firms motivate CEOs for these long-term patent-based innovations by providing them long-term incentive pay such as stock options and restricted stocks (e.g., Lerner and Wulf, 2007; Francis, Hasan, and Sharma, 2011; Mao and Zhang, 2018). On the other hand, routine product development is the introduction of a product that is similar to the existing product line of a firm, which can easily draw market attention (Levinthal and March, 1993). It also provides greater and more certain benefits in the short run, improving present returns (March, 1991). Thus, routine product development acts as a short-term innovation.

We then explore the trade-off effects of ITIs on product innovation created through patenting technologies (long-term innovation) and routine product development (short-term innovation). In our empirical tests, we first partial out the effect of patenting technologies from our product innovation measure and obtain a measure of routine product development.[29] We then separately explore how ITIs affect patent-based innovation and routine product development activities. Interestingly, we find that ITIs negatively affect patent-based innovation (long-term) and positively affect routine product development activities (short-term). Managers tend to find some short-cut ways to enhance their reputation (Narayanan, 1985). Therefore, especially when considering CEO tenure, CEOs seeking to move up might refrain from attempting toilsome patenting activities as they require extensive managerial effort and time, and could instead opt for short-term routine product development activities, which might lead CEOs to gain success in a shorter period.[30] Consistent with the above discussion, we find that the probability of the CEO being promoted to another firm is larger when she employs more myopic innovation strategies.

Although Coles et al. (2018) highlight the value-enhancing outcomes of tournament incentives, our work identifies a negative impact of ITIs. We find that ITIs provide an incentive

[29] We use four measures of patent-based innovation: number of patents, innovation efficiency, number of citations, and market value of patent. We regress our product innovation measure on the lagged five years' number of registered patents and define the error term from this regression as routine product development.

[30] The median CEO tenure is 5 years in our sample.

for CEOs to engage in more routine product innovation activities while discouraging patenting activities. These findings indicate that ITIs are not always value-enhancing. In this respect, this essay contributes to a strand of literature that documents the existence of adverse impacts of ITIs (e.g., Kubick et al., 2020; Kubick and Lockhart, 2020). Last but not least, most of existing managerial short-termism literature focuses on CEO compensation characteristics, contract horizon (e.g., Gryglewicz, Mayer, and Morellec, 2019; Marinovic and Varas, 2019), stock market pressure (e.g., Stein, 1989; Gao, Hsu, and Li, 2018), or takeover threat (e.g., Stein, 1988; Chemmanur and Tian, 2018). Our study contributes to this literature by finding a new motive of short-termism that arises from the external CEO labor market tournament.

III.2 Hypotheses development

Compared with outsider shareholders, managers are less diversified and thus are exposed to more firm-specific risk. Therefore, they may eschew risky projects with positive net present values if they are risk-averse (e.g., Smith and Stulz, 1985; Lambert, Larcker, and Verrecchia, 1991). However, ITIs can provide a similar convex payoff to that of options since the job market tournament winner earns the pay gap while others win nothing. As shown by Coles et al. (2018; 2020), this option-like feature leads to riskier firm policies. Therefore, the risk-taking incentives provided by ITIs may encourage CEOs to engage in product innovation activities.

Based on the above discussion, we posit hypothesis *H1*:

H1: CEOs exhibit higher product innovations when the size of the CEO tournament prize is larger.

An interesting question is whether managers' short-term concerns affects the relation between ITIs and product innovation. Career concerns (Narayanan, 1985), concerns about short -

term stock prices (Stein, 1989), generating high earnings in the short-run (Ferreira, Manso, and Silva, 2014), takeover threats (Stein, 1988), herding behavior (Zwiebel, 1995), shortness of CEO contract horizons (Gonzalez-Uribe and Groen-Xu, 2017) and the CEO's vesting equity grants (Edmans, Fang and Lewellen, 2020) may compel executives to choose less revolutionary projects with a shorter time span that are more easily communicated to stock market investors. Similarly, Gao et al. (2018) find that compared with private firms, public firms' patents are less revolutionary because of the shorter investment horizon in the public stock market. Also, Drucker (1986) reports that the stock market emphasis on short-term accounting earnings is accused of the reduction in long-term investment by 82% of CEOs working in U.S. firms.

Product innovation involves both 'routine' tasks such as improvements in existing products and technological innovation in the form of patents. Routine product development is more visible to investors than technological innovation since firms report their product development in financial reports and new product development news is constantly covered by the media. In contrast, patent applications are reported on USPTO's website and take years to be approved. Moreover, technological innovation in the form of patents is a long-term investment. It also requires significant managerial effort, talent, and commitment to generate patents and convert them into new products and service (Aghion and Tirole, 1994; Manso, 2011). The external job market opportunities provided by ITIs might motivate short-termism since most CEO employment contracts are within five years (Cziraki and Groen-Xu, 2020). To move up to the leading firms within a short time, the CEO may invest more in short-term routine tasks involving the development of the firm's existing products that can quickly draw market attention and boost firm profitability, instead of investing in patenting activities which take more time and need long-term managerial commitment. Similarly, Chemmanur and Tian (2018) document a tendency of managers to invest less in long-term patenting activities and involve more in routine activities offering faster and more certain returns when they are exposed to more short-term pressures stemming from stock markets. Moreover, managers seek short-term aims and prefer investments that have faster paybacks to intensify their reputation (Narayanan, 1985). Consistent with these arguments, Huang et al. (2020) find that CEOs with larger ITIs have a higher propensity to engage in earnings manipulations such as meeting or narrowly beating consensus analyst earnings forecasts and increasing abnormal accruals. Therefore, the industry tournament prize might serve as a short-term motive to enhance the CEO's own reputation, thus CEOs may conduct more incremental product development to win the tournament prize so that she can move up in a shorter time. Levinthal and March (1993) allege that incremental innovation to satisfy the demands of existing customers or markets generates prompt achievement.

This discussion leads to the following hypotheses:

H2: There is a negative relation between ITIs and innovation through patenting activities (long-term innovation).

H3: There is a positive relation between ITIs and routine product development activities (short-term innovation).

Another interesting question is whether the effect of ITIs on product innovation is shaped by the product market competition. In competitive industries, the higher number of rivals causes a fiercer tournament among CEOs. Moreover, firms in such industries have similar products and thus the CEO may need product differentiation to make their products more competitive in the market, which can boost her probability of winning the tournament. Jung and Subramanian (2017) find that firms in competitive industries have a larger demand for talented CEOs who can bring in different skills and pioneering ideas to change the firm, making the labor market for CEO talent more competitive and thus increasing the mobility of CEOs. Therefore, the effect of ITIs on product innovation is expected to be stronger in firms that are in a more competitive market

Furthermore, Hoberg et al. (2014) find that product market competition causes firms to hold more cash. Therefore, firms facing product market competition can use the accumulated cash to obtain product market benefits. Accordingly, as firms can deploy the accumulated cash for product innovation, product market competition can also potentially strengthen the relation between ITIs and product innovation. Then we posit the hypothesis below:

H4: The positive relation between of ITIs and product innovation is more significant for firms facing higher product market competition.

III.3 Data and summary statistics

III.3.1 Data sources

The SEC filings started in 1994, but we need the past two years' financial information, thus, we start the sample at 1996. We restrict our sample up to 2012 to address the truncation bias in patent application data (Hall, Jaffe, and Trajtenberg, 2001; 2005). We construct product innovation via interpreting 10-K statements (annual reports) from textual analysis. 10-K statements are downloaded from the U.S. SEC's EDGAR. CEO pay data is downloaded from ExecuComp. We obtain stock data from CRSP and firm financial statement items (or financial ratios) data from Compustat. Our final sample includes 1,593 firms (12,569 firm-year observations) that have information on patent filings, excluding financial and utility firms. We discuss variable construction in the following sections.

III.3.2 Industry tournament incentives

Following Coles et al. (2018) and Kubick and Lockhart (2020), we compute ITIs as the total compensation of the second highest paid CEO's in the firm's industry less the firm's CEO's total compensation, which is denoted as *Ind_Pay_Gap*. Our main analysis applies the FF30 and SIC3 industry classifications.[31]

III.3.3 Dependent variables

1). Product innovation

Item 101 of Regulation S-K by the SEC requires the U.S. public firms to report the major products and services they provide to the market in their 10-K's business descriptions every year.[32] In addition, product descriptions in 10-Ks, usually stated in Item 1 or Item 1A, are legally required to be accurate and current (Hoberg et al., 2014). Hoberg and Phillips (2010) and Li, Lu, and Phillips (2019) use the growth rate of the number of words in the product description section of 10-K to measure new product announcements. Their measure can only capture product introductions when the product description size is larger in the subsequent year. However, a firm may change product composition without an increase in the size of the product description text. Also, this method does not account for changes in product composition. Thus, the logarithmic growth in the number of words in the product description section may not give a good proxy for product innovation.

We improve this measure by exploiting changes in the product market space rather than just an increase in the size of product descriptions. Our text-based product innovation measure is

---

[31] We use FF30 industry classification following Coles et al. (2018). Usage of SIC3 industry classification is motivated by Huang et al. (2019). SIC3 industry classification represents more concentrated industry classification and is used in Faulkender and Yang (2010) who uses peer group CEO compensation metrics.

[32] Documented on Electronic Code of Federal Regulations website: www.ecfr.gov.

based on the product differentiation computed using the cosine similarity method.[33] For each firm, product differentiation is defined as the change in the use of unique words in the firm's product description from time *t* to time *t+i*. The product descriptions in 10-Ks are supposed to have sufficient information on all the significant products and services, and the difference between two years' product descriptions is likely due to new product innovation. This text-based measure also serves as a continuous measure of product innovation due to the availability of continuous product and services changes through 10-Ks. Firms mention their important trademarks in the product description sections with special HTML tags. Our text-based measure of product innovation also captures product development through trademarks.

To compute the text-based product innovation proxy, first, 10-Ks are downloaded from the U.S. EDGAR database for sample firms using Central Index Key (CIK) numbers.[34] Product descriptions (reported in the Business Description section as Item 1 or Item 1A) are extracted from all required 10-Ks. Firm-specific updates in the existing products are captured using the help of trademark text characters. For example, Apple Inc. has "iPhone" as a trademark text character registered on USPTO, but "iPhone 5", "iPhone 6", and "iPhone 7" are the new products associated with the trademark "iPhone." In product description text, we consider "iPhone5", "iPhone6", and "iPhone7" as different products by eliminating space between the product and its version using a code. We also track revisions in trademark text characters in the product description text. For example, Apple Inc. has "OS X" and "OS X YOSEMITE" as two registered trademark characters in USPTO's trademark database. These two trademarks are also documented in the product descriptions of Apple Inc. An automated script identifies these revisions in the trademarks and

[33] We follow Hoberg and Phillips (2010) to calculate product differentiation.

[34] We use 10-K variants with the form types 10-K, 10-KSB, 10KSB, 10KSB40, 10-K405, 10-KT, and 10KT405.

considers them as two separate words in the product description text. Lastly, product description text is cleaned using a standard procedure followed in textual analysis literature.[35]

Next, this cleaned product description text is converted into a list of unique words for year *t*. Two unique word lists generated for a firm at time *t*–1 and *t* are used for computing the product innovation measure. The two-word lists are combined to form a main dictionary that consists of unique words from both the lists. Then, a binary *N-vector* is constructed separately for these two-word lists where each element of the *N-vector* is set to 1 if a given word in the word list is present in the main dictionary. These two binary *N*-vectors are associated with periods *t*–1 and *t*. For each period, the binary *N-vector* is denoted by *P* and normalized to have a unit length:

$$V = \frac{P}{\sqrt{P \times P^T}} \tag{1}$$

The product similarity for a firm at period *t* is calculated as

$$Prod\_Simi_t = V_{t-1} \times V_t^T, \tag{2}$$

and the product innovation at *t* is calculated as

$$Prod\_Innov_t = 1 - Prod\_Simi_t. \tag{3}$$

Thus, for each firm, *Prod_Innov* is a change in the product space from the previous year to the current year and is bounded between zero and one. It is equal to zero for firms that experience

[35] First, common words are deleted from product descriptions that are used by more than 25 percent of all the firms in the same year. Then, stop words, geographical words, country names, city names, and people names and surnames are removed (numbers are also deleted). Further, words are stemmed using Porter stemming algorithm. We omit product descriptions that have fewer than 20 unique words. Finally, only nouns and proper nouns (defined by wiktionary.org) along with the trademark characters and the revisions in product names are considered in the cleaned version of product description texts.

no change in their product market space. Higher values of *Prod_Innov* denote a larger change in the firm's product space, which is equivalent to higher product innovations.[36]

To illustrate the intuition behind what *Prod_Innov* measures, suppose a firm uses eight words in year *t* and five words to describe its products in year *t*–1. Based on the method in the table below, we obtain $Prod\_Simi_t$ as 0.79 and $Prod\_Innov_t$ as 0.21, as defined in equations (2) and (3), respectively. We see that the firm has three new words in period *t*, which potentially represents new products or services and thereby suggests product innovation.

Word	*Year (t–1)*	*Year (t)*	*P(t–1)*	*P(t)*	*V(t–1)*	*V(t)*
computer	Yes	Yes	1	1	0.447	0.354
mouse	Yes	Yes	1	1	0.447	0.354
motherboard	Yes	Yes	1	1	0.447	0.354
chip	Yes	Yes	1	1	0.447	0.354
signal	Yes	Yes	1	1	0.447	0.354
bluetooth	No	Yes	0	1	0.000	0.354
sensor	No	Yes	0	1	0.000	0.354
wireless	No	Yes	0	1	0.000	0.354

2) Product announcements variable

We follow Mukherjee et al.'s (2017) methodology to obtain a new product announcement variable for our sample period.[37] First, we search the LexisNexis news database for corporate news

[36] To construct $Prod\_Inn_{t+1}$ ($Prod\_Inn_{t+2}$) measure over *t*+1 (*t*+2), we compare product description of a firm at year *t* with that of *t*+1 (*t*+2).

[37] We thank Alminas Žaldokas for sharing product announcements data up to 2006. We extend this data up to 2012 following Mukherjee et al. (2017).

labeled under the subject "New Products" and containing new product keywords such as "Launch," "Product," "Introduce," "Begin," and "Unveil" in their headlines. We download the news based on company ticker names with relevance scores greater than 85% and then use the one-factor model to conduct event studies to obtain abnormal returns.[38] We then only keep the product announcements in a fiscal year in which the stock return exceeds its 75th percentile. This method provides a count on major new products introduced by the firm. Our sample for the new product announcement variable contains firms with the intersection of patenting firms and firms having information on product announcements. Following the innovation literature, we assign zeros to firm-year observations with missing product announcement information. We then use the natural log of 1 plus the total number of product announcements by a firm in a fiscal year and denote this variable as *Prod_Announce*.

3). Patent-based innovation variables

We first obtain patent data for our sample period from Kogan, Papanikolaou, Seru, and Stoffman (2017).[39] Patent data suffers from truncation problems (Hall et al., 2001; 2005). Although we restrict our sample up to 2012, we further address this issue by using the adjusted number of patent-based variables, as discussed below.

Following the innovation literature, we use four variables to study patent-based technological innovation. First, we define *nPats* as the natural log of 1 + the total adjusted number of patent applied (and eventually granted) by a firm in a fiscal year, we fill missing values with 0. This variable represents the quantity of innovation output. To compute the adjusted number of

[38] Following Mukherjee et al. (2017), we first fit a market model over the window (-246, -30) around the announcement date to obtain the beta for the firm's stock, and then we calculate cumulative abnormal returns over a 3-day period (-1,1).

[39] We are grateful of Noah Stoffman for making updated patent data readily available on his personal website.

patents, following Hall et al. (2001), we divide the amount of patents of the firm by the mean amount of patents in the same 3-digit technology class as the patent applied by all firms in the same year.[40] Second, *InnovEff* is measured as the natural log of $1 +$ the ratio of the total number of patents applied in a given year divided by the previous year's R&D (research and development) expenditures. This variable captures the efficient usage of financial resources spent on R&D to generate patents (Shen and Zhang, 2018). The third variable, *nCits*, is defined as the natural log of $1 +$ the entire quantity of adjusted citations received for the patents applied (and eventually granted) by a firm in a fiscal year, and we fill the missing values with 0. This variable represents the quality of innovation output. The adjusted number of citations is calculated as the raw number of patent citations scaled by the average patent citations in the year-and-technology class in which the patent belongs (Hall et al., 2001; 2005). This weighting adjustment for citations corrects for the truncation bias because patent citations are accumulated during many years after the patent is granted. The last variable, *PatValue*, is the natural log of total economic value generated by all the patents applied by a firm in the year plus one (Kogan et al., 2017). This variable represents the market value generated by patents.

III.3.4 Control variables

In all the regressions, we control for internal tournament incentives for other executives. Following Kale et al. (2009) and Shen and Zhang (2018), the internal tournament incentives, *Firm_Gap*, is measured the CEO's total pay package less the median value of other executives' total pay package. We also include the natural logarithm of CEO delta and the natural logarithm

[40] On average it takes 3.27 years from the time a patent application is filed in USPTO until the time it is approved in our sample, and therefore some patents that have already been applied for may not yet appear in the sample (e.g., Hall et al., 2001; 2005). This weighting adjustment corrects for the truncation bias in patent grants.

of CEO vega, *Ln(CEO_Vega)*.[41] The other firm characteristics include measures of firm size (the natural logarithm of total assets), investment in innovation (the ratio of R&D expenditures to total assets), profitability (Return on Asset), asset tangibility (the ratio of PPE, or net property, plant, and equipment, to total assets), leverage (the ratio of book leverage to by total assets), etc. See APPENDIX D for detailed definitions of all the variables. In all our regression models, we control for year dummies and industry dummies.

III.3.5 Product market competition

We also study whether the effect of ITIs on product innovation varies with different extent of competition. We use the product market fluidity introduced by Hoberg et al. (2014) as a proxy for product market competition. The product market fluidity, *Prodmkt_Fluid*, is a measure of firm-level product market competition based on the description of a firm's products, and competitor move in their 10-Ks. A larger magnitude of product market fluidity denotes that a firm is facing more competitive threats from its rivals, in other words, that rivals are creating more innovative products.

III.3.6 Summary statistics

The main statistics for our main variables are summarized in Table 24. As displayed in Table 24, the average value of the text-based product innovation measure, *Prod_Innov*, is 0.14 (standard deviation of 0.09) with the 75th percentile of 0.18. Also, the means (medians) of product announcement variable, *Prod_Announce,* number of patents, *nPats*, innovative efficiency, *InnovEff,* number of citations, *nCits,* and patent value, *PatValue*, are 0.38 (0.00), 0.85 (0.30), 0.07

[41] We use SAS codes in Naveen's website to compute CEO delta and vega. We corrected some minor mistakes of the original codes.

(0.03), 1.56 (0.72), and 0.10 (0.02), separately. The mean (median) of ITIs based on FF 30 industry, *Ind_Pay_Gap* is \$25.15 million (\$17.96 million). The median (averages) of CEO Vega and CEO Delta are \$56,927 (\$136,128) and \$202,615 (\$791,810), respectively, and the magnitudes "closely resembles those in Cole, Daniel, and Naveen (2006).[42]

Panel B shows a Pearson correlation matrix for the validity of our text-based product innovation variable. Our text-based product innovation proxy, *Prod_Innov*, is positively correlated with *nPats*, *nCits*, *PatValue*, *R&D*, and *Prod_Announce*, which is in harmony with the view that the larger sensitivity of CEO wealth to stock volatility causes CEOs to pursue more risks(Coles et al., 2006). The correlation between *Prod_Innov* and product market fluidity measure, *Prodmkt_Fluid*, is significantly positive. This positive correlation is consistent with Le, Vo, and Le (2018) who find that firms facing high product market threats exhibit higher innovation activities. Overall, these results provide validity for our text-based product innovation measure.

III.4 Empirical results

III.4.1 ITIs and product innovation

We first study the effects of ITIs on product innovation using OLS regression as well as 2SLS approach. To address serial correlation and heterogeneity in the idiosyncratic errors, standard errors are clustered at firm level in all regressions.

---

[42] We use the variable *SHROWN_EXCL_OPTIONS* in ExecuComp to measure the number of stock grants, which includes both restricted and unrestricted shares. For stock options, we use the Black-Scholes model to compute their values. Following Core and Guay (1999) and Coles et al. (2013), we separately compute the option deltas and vegas for the existing options and new option grants. For the existing unvested options, we use the exercise date and the fiscal year to compute the maturity. The maturity of vested options is assumed to be three years less than that of unvested options. We assume that the newly granted options have the same maturity as the unvested options. If the maturity is longer than 10 years, we assume that it is equal to 10 years. The risk-free rate is the yield for Treasury constant maturities. The estimated dividend yields and volatilities are given in ExecuComp. The vega for stock grants is zero, so we only use the option portfolios to calculate vega.

First, we employ OLS regression to test whether ITIs influence product innovation. The estimated OLS model is:

$$Prod\_Innov_{i,t+j} = \alpha_i + \beta_1 Ln(Ind\_Pay\_Gap)_{i,t} + \beta_2 Ln(Firm\_Gap)_{i,t} \\ +\beta_3 Ln(CEO\_Delta)_{i,t} + \beta_4 Ln(CEO\_Vega)_{i,t} \\ + \gamma Controls_{i,t} \tag{4}$$

where i indexes firms, t indexes years, and j ranges from 1 to 2.[43] The dependent variable *Prod_Innov* measures product innovation based on the difference between the current year's product description to the previous year's description. See APPENDIX D for detailed definition on other variables.

We next consider the scenario in which the relation between ITIs and product innovation may be endogenous. We use 2SLS estimation to test whether ITIs influence product innovation. The first-stage regression used to compute predicted values for ITIs is

$$Ln(Ind\_Pay\_Gap)_{i,t} = \alpha_i + \theta_1 Ln(Ind\_CEO\_Comp)_{i,t} + \theta_2 Ln(Geo\_Pay\_Rank)_{i,t} \\ + \delta_1 Ln(Firm\_Gap)_{i,t} + \delta_2 Ln(CEO\_Delta)_{i,t} + \\ \delta_3 Ln(CEO\_Vega)_{i,t} + \gamma Controls_{i,t}. \tag{5}$$

We follow Coles et al. (2018) and Kubick et al. (2020) to use the summation of total compensation for all the other CEOs in firms that share the same industry classification code (excluding the top-1 paid CEO), *Ind_CEO_Comp*, and the rank of a CEO's total compensation among all other CEOs from different industries who work at firms whose headquartered are no more than 250-km from the firm, *Geo_Pay_Rank*, as instrumental variables for ITI. The rank variable is normalized to have values between 0 and 1.

[43] As it takes a significant amount of time to generate new products, we construct our *Prod_Innov* measures over t+1 and t+2 following Hoberg and Phillips (2010) and Li et al. (2019). To construct *Prod_Innov* measure over t+1 (t+2), we compare product description of a firm at year t with t+1 (t+2) The results are similar when we examine product innovation from year t to year t+3.

The main findings are reported in Table 25. Models (1)–(4) present results obtained using the FF30 industry classifications to form ITIs measure, and Models (5)–(8) present results using the SIC3 industry classification. Models (1) and (5) show the results regarding OLS regressions. Models 2–4 (6–8) shows the results regarding 2SLS regressions in FF30 (SIC3) industry classifications. The Hausman test statistics confirms the endogeneity of the variable *Ln(Ind_Pay_Gap)*. The significant coefficient on *Ln(Ind_CEO_Comp)* and the statistically significant *F*-statistics in the first stages of 2SLS regressions imply that the instrument variables satisfy the relevance criterion. Hansen's *J*-test suggest that the two instruments used are unlikely to be endogenous.

The coefficients on *Ln(Ind_Pay_Gap)* are always positive and statistically significant at the OLS regression (Model 1) and at the second stage of 2SLS regressions (Models 3–4 and 7–8). As for economic significance, the second stage of 2SLS indicates that an increase of one standard deviation in *Ind_Pay_Gap* around its mean results in around a 16.75% (25.29%) standard deviation increase in the $Prod\_Innov_{t+1}$ variable for FF30 (SIC3) industry classification.[44] The above results are in line with our hypothesis *H1* that the level of product innovation positively affects the amount of the industry tournament prize. The coefficients on *Ln(Firm_Gap)* are positive, but the magnitudes are much smaller than those on *Ln(Ind_Pay_Gap)*. This confirms our conjecture that CEOs play a more important role than other executives in setting product innovation policies. At the second stage of 2SLS regressions, there is always hya positive relation between *R&D* and *Prod_Innov*, which means that more R&D expenditures lead to more product innovation. Additionally, larger firms, firms with less profitability, firms facing fiercer product market

[44] We use the following method to compute economic significance:
$$\frac{[Ln(mean\ of\ Ind\_Pay\_Gap + 0.5std) - Ln(mean\ of\ Ind\_Pay\_Gap - 0.5std)] \times coef\ on\ Ln(Ind\_Pay\_Gap)}{std(Prod\_Innov)}.$$

competition, and older firms tend to produce higher product innovations. The coefficients on the control variables for our text-based product innovation measure are often consistent with the innovation literature. This also provides validity to our measure of product innovation.

Overall, the results in Table 25 are in accordance with the null hypothesis that CEOs are incentivized to undertake more innovative product activities that could help them with career promotion when the industry pay gap is large.

III.4.2 The trade-off effects of ITIs on short-term versus long-term innovation activities

In this section, we investigate how ITIs influence long-term versus short-term innovation strategies. Product innovations could arise from patent-based innovation or routine product development. A firm can use its existing granted patents to produce new goods and services or to improve existing ones. In addition, the firm may innovate its products through routine product development activities that do not need any patenting technologies. In this section, we separate the effect of patenting technologies, the long-term innovation effect, from our main text-based product innovation measure to obtain a variation in the product innovation through routine product development activities, the short-term innovation effect. We then separately analyze how ITIs affect patenting technologies (long-term innovation) versus routine product development activities (short-term innovation). We report three years gap between ITIs and patent-based variables following the previous literature (e.g., Fang et al., 2014; Chemmanur and Tian, 2018).

The results regarding patent-based variables are shown in Table 26. The analyses are performed under FF30 and SIC3 industry classifications in Panel A and B, respectively. The coefficients on the *Ln(Ind_Pay_Gap)* in the second stage of Models (2)–(5) are significantly negative at the 1% level. The negative effect of ITIs on patent-based innovation is also economically significant. Under FF30 industry classifications, if *Ln(Ind_Pay_Gap)* rises by one standard deviation, it reduces *nPats b*y 13.23% (0.137×0.965), a 1.93% (0.020×0.965) decrease in *InnovEff*, a 22.40% (0.232×0.965) decrease in *nCits*, and a 1.74% (0.018×0.965) decrease in *PatValue* in the subsequent years.[45]

Next, we explore the effect of ITIs on routine product development activities. We partial out the effect of patenting technologies from our product innovation measure and obtain a measure of short-term routine product development activities. To do so, we first regress the text-based product innovation measure on the natural log of (the number of patents applied (and eventually granted) by the firm in the last five years plus 1). We use the following OLS specification using Newey–West standard errors with five lags:

$$Prod\_Innov_{i,t} = \alpha_i + \beta_1 Ln\left(1 + \sum_{s=1}^{5} \#Patents_{i,t-s}\right) + \varepsilon_{i,t}. \tag{5}$$

We then obtain the error terms from this regression and define them as a measure for routine product development activities, denoted as *NonPat_ProdDev* since this variable excludes patenting technologies. We then run 2SLS models similar in Table 2 with this measure of routine product development as our dependent variable.

The results are documented in Table 27. We get positive and significant coefficients on *Ln(Ind_Pay_Gap)* in all the models of FF30 and SIC3 industry classifications at the conventional significance levels. These results suggest that ITIs also affect product innovation that does not stem from patents. In respect of economic significance, the second stage of 2SLS indicates that a

[45] The standard deviation of *Ln(Ind_Pay_Gap)* is 0.965.

one standard deviation increase in *Ind_Pay_Gap* around its mean results in around 11.02% (18.49%) standard deviation increase in the *NonPat_ProdDev* variable for FF30 (SIC3) industry classification.[46]

The results illustrated in Table 26 and Table 27 suggest that CEOs motivated by ITIs have a tendency to engage in short-term routine product development activities and to avoid long-term patenting activities. These results are parallel to hypotheses *H2* and *H3*. Although ITIs have an option-like convex payoff motivating risky product innovation activities, they are more likely to induce short-term product improvement activities, which generate faster payoff than long-term patenting activities. These results indicate that short-termism plays an important role in the incentive effects of industry tournaments.

IV.4.3 The effect of ITIs on product innovation conditional on product market competition

We test how the effect of ITIs on product innovation is impacted by product market competition faced by a firm in this section. We use the median values of product market fluidity to separate the whole sample to two subsamples and run separate 2SLS regressions for these two subsamples.

Table 28 reports our findings on these regressions. As shown in the table, the coefficients on *Ln(Ind_Pay_Gap)* in Models (2) and (4) are much larger and statistically significant than those in Models (1) and (3), indicating that the effect of ITIs on product innovation is larger for the subsample with the higher *Prodmkt_Fluid.* Consistent with our hypothesis H4, Table 28 suggests

[46] The standard deviation of *NonPat_ProdDev* is 0.093.

that the positive influence of ITIs on product innovation is more notable for firms facing higher product market competition.

IV4.4 Myopic innovation strategy and CEO turnover

In this section, we examine whether CEOs who focus more on routine product development strategies indeed win the tournament prize, or in other words, move to another peer firm. Table 29 shows the effects of myopic innovation strategy on CEO turnover, which is equal to one if the current CEO moves to another Execucomp firm in the next three years, otherwise set to zero. Column (1) shows results when the independent variable in interest is routine product development (*NonPat_ProdDev*). In column (2), we use a dummy variable *High_Myopic_Innov* equal to one (zero) if a firm has *NonPat_ProdDev* above (below) its year-industry median. In column (3), we interact this dummy variable with the industry pay gap. As shown in column (1) and column (2) of Table 29, the coefficients on *NonPat_ProdDev* and *High_Myopic_Innov* are all significantly positive, suggesting that CEOs with more myopic product innovation strategies are more likely to move to peer firms. The coefficient on the multiplication of the high myopic innovation dummy and industry pay gap is significantly positive in column (3). This suggests that CEOs experiencing higher tournament incentives are more likely to be promoted when they pursue higher myopic innovation strategies in the current firm.[47]

[47] We acknowledge that there are potential pitfalls in our empirical design. Due to data availability, we are only able to identify the turnovers within S&P 1500 firms. During our sample period, there are only 49 turnovers within S&P 1500 firms. Due to the infrequency of CEO turnovers and for the statistical significance, we do not restrict the CEOs' original firm and the new firm to be within the same industry or CEOs earning a higher compensation in the new firm.

III.5 Robustness and additional tests

First, we use a semi-natural experiment as a shock to the association between ITIs and product innovation. Specially, we exploit state-level implementation of noncompetition agreements. Under these agreements, the employees (usually top managers) agree not to enter into or start a similar business that competes against the current company. CEOs who work in firms located in the states that have enforced these agreements are likely to have a lower motivation to move to rival firms; thus, the external job market is less likely to affect their product innovation policies. Therefore, the change in the enforceability of noncompetition agreements provides a shock to ITIs, but it is unlikely to affect product innovation policies directly. We obtain data regarding the alterations in state-level implementation up to 2012 from Huang et al. (2019).[48] Following Huang et al. (2019), we perform difference-in-differences methods for subsamples that involve the number of in-state competitors more than 25th, 50th, and 75th percentiles since the effect of the implementation of noncompetition agreements on the labor market can differ in the number of state competitors. Garmaise (2011) finds that when the number of competitors is larger in a particular state, the noncompetition agreements will be more effective and thus it makes industry tournaments less effective. Table 30 list the results. As expected, we find a significantly negative impact of noncompetition agreement implementation on the relation between ITIs and product innovation, and this negative impact enhances with the increase in the in-state number of competitors.

Next, our product innovation measure using 10-Ks business description may be susceptible to window dressing when firms are unable to produce patent-based innovation. Therefore, we also

[48] We use firms' historical headquartered state information obtained from 10-K headers.

examine our main hypothesis with the use of another proxy for product innovation, the number of new product announcements (Mukherjee et al., 2017). The new product announcement variable, *Prod_Announce*, is the natural log of (1+ the total quantity of a firm's product announcements in a fiscal year). This variable is likely to be less prone to window dressing. Using this measure as a dependent variable, we run 2SLS regressions similar to those presented in Table 25. The results are reported in Table 31. As shown in the table, the coefficients on *Ln(Ind_Pay_Gap)* are positive and statistically significantly for both FF30 and SIC3 industry classifications.[49] These results implicate that as external job market tournament incentives increase, CEOs are inclined to announce more new products.

Next, we run our main model specifications for the impacts of ITIs on product innovation and patent-based innovation with year dummies and firm dummies. The results are listed in Table 32, and they closely resemble the results in Table 25 and Table 26 that include industry dummies and year dummies. As presented in Panel A of Table 32, the coefficients on *Ln(Ind_Pay_Gap)* are positive and statistically significantly, where we test the impacts of ITIs on product innovation. In Panel B, the coefficients on *Ln(Ind_Pay_Gap)* are significantly negative, except in Models (7) and (8), where we examine the impacts of ITIs on patent-based innovation. These results exhibit that our main findings persist when including firm and year dummies.

We then use FF30 (SIC3) size-median industry classifications to compute ITIs measure and examine the impacts of ITIs on product innovation and patent-based innovation, so that a peer group can be comprised of firms with more similar sizes. Last, we scale ITIs by total compensation

[49] These results are also consistent and economically large if we use product innovation at year *t+2*. If *Ln(Ind_Pay_Gap)* increases by one standard deviation, new product announcements in the subsequent year increases by 7.82% (9.17%) for FF30 (SIC3) industry classification.

to account for the relative importance of pay gap in total compensation and repeat the analyses in Table 25 and Table 26. The results are shown in

Table 33 and

Table 34, separately, and they are qualitatively similar to those in Table 25 and Table 26.

III.6 Conclusion

Motived by Hoberg and Philips (2010), we analyze product descriptions reported in 10-K statements based on automized textual analysis to measure product innovation. Specifically, we exploit the changes in the product market vocabulary of a firm over time to gauge its product innovation output. We take advantage of the rich and continuous information on the product descriptions in 10-Ks because they are required by the SEC to be disclosed. Using this text-based measure of innovation outcome, we find that ITIs influence product innovation positively. This effect is more evident for CEOs facing higher product market competition and having a higher probability of moving to the leading firm within the industry.

Furthermore, we explore the trade-off effects of ITIs on product innovation created through patenting technologies versus routine product development. We discover a negative association between ITIs and patent-based innovation and a positive association between ITIs and routine product development activities. This result suggests that CEOs motivated by moving up to the top firm are discouraged from patenting innovation as it takes a long time to generate income for the firm, but they are encouraged for short-term routine product development activities that can intensify their reputation in a short time.

Overall, our analyses indicate that the external job market motivates CEOs to promote product innovation. However, the short-term nature of industry tournaments induces CEOs to conduct more routine product development activities and reduce long-term patent-based innovation.

REFERENCES

Aghion, P., & Tirole, J. (1994). The management of innovation. The Quarterly Journal of Economics, 109, 1185-1209.

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and momentum everywhere. The Journal of Finance, 68, 929-985.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. The Journal of Finance, 61, 1645-1680.

Bakshi, G., Gao, X., & Rossi, A. G. (2019). Understanding the sources of risk underlying the cross section of commodity returns. Management Science, 65, 619-641.

Baranchuk, N., Kieschnick, R., & Moussawi, R. (2014). Motivating innovation in newly public firms. Journal of Financial Economics, 111, 578-588.

Basak, S., & Pavlova, A. (2016). A model of financialization of commodities. The Journal of Finance, 71, 1511-1556.

Basu, D., & Miffre, J. (2013). Capturing the risk premium of commodity futures: The role of hedging pressure. Journal of Banking & Finance, 37, 2652-2664.

Belloni, A., Chernozhukov, V., & others. (2013). Least squares after model selection in high-dimensional sparse models. Bernoulli, 19, 521-547.

Bettis, J. C., Bizjak, J. M., & Lemmon, M. L. (2005). Exercise behavior, valuation, and the incentive effects of employee stock options. Journal of Financial Economics, 76, 445-470.

Bianchi, R. J., Drew, M. E., & Fan, J. H. (2016). Commodities momentum: A behavioral perspective. Journal of Banking & Finance, 72, 133-150.

Boehe, D. M., & Cruz, L. B. (2010). Corporate social responsibility, product differentiation strategy and export performance. Journal of Business ethics, 91, 325-346.

Boons, M., & Prado, M. P. (2019). Basis-momentum. The Journal of Finance, 74, 239-279.

Bosch, D., & Pradkhan, E. (2017). Trading Activity and Rate of Convergence in Commodity Futures Markets. Journal of Futures Markets, 37, 930-938.

Breiman, L. (2001). Random forests. Machine learning, 45, 5-32.

Brown, D. P., & Jennings, R. H. (1989). On technical analysis. The Review of Financial Studies, 2, 527-551.

Burns, N., Minnick, K., & Starks, L. (2017). CEO tournaments: A cross-country analysis of causes, cultural influences, and consequences. Journal of Financial and Quantitative Analysis, 52, 519-551.

Chemmanur, T. J., & Tian, X. (2018). Do antitakeover provisions spur corporate innovation? A regression discontinuity analysis. Journal of Financial and Quantitative Analysis, 53, 1163-1194.

Chen, S.-T., Kuo, H.-I., & Chen, C.-C. (2010). Modeling the relationship between the oil price and global food prices. Applied Energy, 87, 2517-2525.

Chinco, A., Clark-Joseph, A. D., & Ye, M. (2019). Sparse signals in the cross-section of returns. The Journal of Finance, 74, 449-492.

Chordia, T., Subrahmanyam, A., & Tong, Q. (2014). Have capital market anomalies attenuated in the recent era of high liquidity and trading activity? Journal of Accounting and Economics, 58, 41-58.

Ciner, C., Lucey, B., & Yarovaya, L. (2020). Spillovers, integration and causality in LME non-ferrous metal markets. Journal of Commodity Markets, 17, 100079.

Clark, J., & Guy, K. (1998). Innovation and competitiveness: a review: Practitioners' forum. Technology Analysis & Strategic Management, 10, 363-395.

Coad, A., & Rao, R. (2008). Innovation and firm growth in high-tech sectors: A quantile regression approach. Research policy, 37, 633-648.

Coles, J. L., Daniel, N. D., & Naveen, L. (2006). Managerial incentives and risk-taking. Journal of financial Economics, 79, 431-468.

Coles, J. L., Daniel, N., & Naveen, L. (2013). Calculation of compensation incentives and firm-related wealth using Execucomp: Data, program. Tech. rep., and explanation. Working Paper, Arizona State University.

Coles, J. L., Li, Z. F., & Wang, Y. A. (2020). A model of industry tournament incentives. Available at SSRN 3528738.

Coles, J. L., Li, Z., & Wang, A. Y. (2018). Industry tournament incentives. The Review of Financial Studies, 31, 1418-1459.

Core, J., & Guay, W. (1999). The use of equity grants to manage optimal equity incentive levels. Journal of accounting and economics, 28, 151-184.

Corsino, M., & Gabriele, R. (2011). Product innovation and firm growth: evidence from the integrated circuit industry. Industrial and corporate change, 20, 29-56.

Cotter, J., Eyiah-Donkor, E., & Potì, V. (2017). Predictability and diversification benefits of investing in commodity and currency futures. International Review of Financial Analysis, 50, 52-66.

Cziraki, P., & Groen-Xu, M. (2020). CEO turnover and volatility under long-term employment contracts. Journal of Financial and Quantitative Analysis, 55, 1757-1791.

Da, Z., Tang, K., Tao, Y., & Yang, L. (2020). Financialization and commodity market serial dependence. Available at SSRN 3285541.

Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. Journal of Financial Economics, 122, 221-247.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. The Journal of Finance, 53, 1839-1885.

Daskalaki, C., Kostakis, A., & Skiadopoulos, G. (2014). Are there common factors in individual commodity futures returns? Journal of Banking & Finance, 40, 346-363.

DeMiguel, V., Nogales, F. J., & Uppal, R. (2014). Stock return serial dependence and out-of-sample portfolio performance. The Review of Financial Studies, 27, 1031-1073.

Drucker, P. (1986). A crisis of capitalism. Wall Street Journal, 30, 30-31.

Edmans, A., Fang, V. W., & Lewellen, K. A. (2020). Equity vesting and managerial myopia. Oxford University Press.

Efron, B., Hastie, T., Johnstone, I., Tibshirani, R., & others. (2004). Least angle regression. The Annals of statistics, 32, 407-499.

Erb, C. B., & Harvey, C. R. (2006). The strategic and tactical value of commodity futures. Financial Analysts Journal, 62, 69-97.

Erven, T. v., Grünwald, P., & Rooij, S. (2012). Catching up faster by switching sooner: a predictive approach to adaptive estimation with an application to the AIC--BIC dilemma. Journal of the Royal Statistical Society: Series B (Statistical Methodology), 74, 361-417.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33, 3-56.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. Journal of Financial Economics, 116, 1-22.

Fang, V. W., Tian, X., & Tice, S. (2014). Does stock liquidity enhance or impede firm innovation? The Journal of finance, 69, 2085-2125.

Faulkender, M., & Yang, J. (2010). Inside the black box: The role and composition of compensation peer groups. Journal of Financial Economics, 96, 257-270.

Fee, C. E., & Hadlock, C. J. (2004). Management turnover across the corporate hierarchy. Journal of Accounting and Economics, 37, 3-38.

Fernandez-Perez, A., Frijns, B., Fuertes, A.-M., & Miffre, J. (2018). The skewness of commodity futures returns. Journal of Banking & Finance, 86, 143-158.

Ferreira, D., Manso, G., & Silva, A. C. (2014). Incentives to innovate and the decision to go public or private. The Review of Financial Studies, 27, 256-300.

Francis, B. B., Hasan, I., & Sharma, Z. (2011). Incentives and innovation: Evidence from CEO compensation contracts. Bank of Finland Research Discussion Paper.

Freyberger, J., Neuhierl, A., & Weber, M. (2020). Dissecting characteristics nonparametrically. The Review of Financial Studies, 33, 2326-2377.

Friedman, J. H. (2001). Greedy function approximation: a gradient boosting machine. Annals of statistics, 1189-1232.

Gao, H., Hsu, P.-H., & Li, K. (2018). Innovation strategy of private firms. Journal of Financial and Quantitative Analysis, 53, 1-32.

Gao, X., Nardari, F., & others. (2018). Do commodities add economic value in asset allocation? New evidence from time-varying moments. Journal of Financial and Quantitative Analysis, 53, 365-393.

Gargano, A., & Timmermann, A. (2014). Forecasting commodity price indexes using macroeconomic and financial predictors. International Journal of Forecasting, 30, 825-843.

Garmaise, M. J. (2011). Ties that truly bind: Noncompetition agreements, executive compensation, and firm investment. The Journal of Law, Economics, and Organization, 27, 376-425.

Georgopoulou, A., & Wang, J. (2017). The trend is your friend: Time-series momentum strategies across equity and commodity markets. Review of Finance, 21, 1557-1592.

Goel, A. M., & Thakor, A. V. (2008). Overconfidence, CEO selection, and corporate governance. The Journal of Finance, 63, 2737-2784.

Gong, G., Li, L. Y., & Shin, J. Y. (2011). Relative performance evaluation and related peer groups in executive compensation contracts. The Accounting Review, 86, 1007-1043.

Gong, Y., Gozluklu, A. E., & Kim, G. H. (2020). Speculator Spreading Pressure and Commodity Futures Risk Premium. Available at SSRN.

Gonzalez-Uribe, J., & Groen-Xu, M. (2017). CEO contract horizon and innovation. Available at SSRN 2633763.

Goyal, A., & Jegadeesh, N. (2018). Cross-sectional and time-series tests of return predictability: What is the difference? The Review of Financial Studies, 31, 1784-1824.

Graham, J. R., Harvey, C. R., & Rajgopal, S. (2005). The economic implications of corporate financial reporting. Journal of accounting and economics, 40, 3-73.

Grinblatt, M., & Han, B. (2005). Prospect theory, mental accounting, and momentum. Journal of Financial Economics, 78, 311-339.

Grundy, B. D., & Kim, Y. (2002). Stock market volatility in a heterogeneous information economy. Journal of Financial and Quantitative Analysis, 37, 1-27.

Gryglewicz, S., Mayer, S., & Morellec, E. (2020). Agency conflicts and short-versus long-termism in corporate policies. Journal of Financial Economics, 136, 718-742.

Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. The Review of Financial Studies, 33, 2223-2273.

Guay, W. R. (1999). The sensitivity of CEO wealth to equity risk: an analysis of the magnitude and determinants. Journal of Financial Economics, 53, 43-71.

Guidolin, M., & Pedio, M. (2020). Forecasting commodity futures returns with stepwise regressions: Do commodity-specific factors help? Annals of Operations Research, 1-40.

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. (2001). The NBER patent citation data file: Lessons, insights and methodological tools. Tech. rep., National Bureau of Economic Research.

Hall, B. H., Jaffe, A., & Trajtenberg, M. (2005). Market value and patent citations. RAND Journal of economics, 16-38.

Hamilton, J. D., & Wu, J. C. (2015). Effects of index-fund investing on commodity futures prices. International Economic Review, 56, 187-205.

Han, Y., He, A., Rapach, D., & Zhou, G. (2019). Firm characteristics and expected stock returns. Available at SSRN 3185335.

Han, Y., Hu, T., & Yang, J. (2016). Are there exploitable trends in commodity futures prices? Journal of Banking & Finance, 70, 214-234.

Han, Y., Zhou, G., & Zhu, Y. (2016). A trend factor: Any economic gains from using information over investment horizons? Journal of Financial Economics, 122, 352-375.

Hirshleifer, D. (1990). Hedging pressure and futures price movements in a general equilibrium model. Econometrica: Journal of the Econometric Society, 411-428.

Hjalmarsson, E. (2010). Predicting global stock returns. Journal of Financial and Quantitative Analysis, 45, 49-80.

Hoberg, G., & Phillips, G. (2010). Product market synergies and competition in mergers and acquisitions: A text-based analysis. The Review of Financial Studies, 23, 3773-3811.

Hoberg, G., Phillips, G., & Prabhala, N. (2014). Product market threats, payouts, and financial flexibility. The Journal of Finance, 69, 293-324.

Hollstein, F., Prokopczuk, M., Tharann, B., & Wese Simen, C. (2020). Predicting the Equity Premium around the Globe: Comprehensive Evidence from a Large Sample. Available at SSRN.

Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. The Journal of Finance, 54, 2143-2184.

Huang, D., Li, J., Wang, L., & Zhou, G. (2020). Time series momentum: Is it there? Journal of Financial Economics, 135, 774-794.

Huang, J., Jain, B. A., & Kini, O. (2019). Industry tournament incentives and the product-market benefits of corporate liquidity. Journal of Financial and Quantitative Analysis, 54, 829-876.

Huang, Q., Jiang, F., & Xie, F. (2020). A Dark Side of Industry Tournament Incentives. Available at SSRN 3478660.

Hurst, B., Ooi, Y. H., & Pedersen, L. H. (2017). A century of evidence on trend-following investing. The Journal of Portfolio Management, 44, 15-29.

Hvide, H. K. (2002). Tournament rewards and risk taking. Journal of Labor Economics, 20, 877-898.

Jeffers, J. (2019). The impact of restricting labor mobility on corporate investment and entrepreneurship. Available at SSRN 3040393.

Johnson, T. C. (2002). Rational momentum effects. The Journal of Finance, 57, 585-608.

Jung, H. W., & Subramanian, A. (2017). CEO talent, CEO compensation, and product market competition. Journal of Financial Economics, 125, 48-71.

Kale, J. R., Reis, E., & Venkateswaran, A. (2009). Rank-order tournaments and incentive alignment: The effect on firm performance. The Journal of Finance, 64, 1479-1512.

Kang, W., Rouwenhorst, K. G., & Tang, K. (2020). A tale of two premiums: The role of hedgers and speculators in commodity futures markets. The Journal of Finance, 75, 377-417.

Kaplan, S. N., & Zingales, L. (1997). Do investment-cash flow sensitivities provide useful measures of financing constraints? The quarterly journal of economics, 112, 169-215.

Keynes, J. M. (1930). Treatise on money: Pure theory of money Vol. I. Macmillan, London.

Kim, A. Y., Tse, Y., & Wald, J. K. (2016). Time series momentum and volatility scaling. Journal of Financial Markets, 30, 103-124.

Kini, O., & Williams, R. (2012). Tournament incentives, firm risk, and corporate policies. Journal of Financial Economics, 103, 350-376.

Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological innovation, resource allocation, and growth. The Quarterly Journal of Economics, 132, 665-712.

Kubick, T. R., & Lockhart, G. B. (2020). Industry tournament incentives and stock price crash risk. Financial Management.

Lambert, R. A., Larcker, D. F., & Verrecchia, R. E. (1991). Portfolio considerations in valuing executive compensation. Journal of Accounting Research, 29, 129-149.

Lazear, E. P., & Rosen, S. (1981). Rank-order tournaments as optimum labor contracts. Journal of political Economy, 89, 841-864.

Le Pen, Y., & Sévi, B. (2018). Futures trading and the excess co-movement of commodity prices. Review of Finance, 22, 381-418.

Le, D. V., Le, H. T., & Van Vo, L. (2021). The bright side of product market threats: The case of innovation. International Review of Economics & Finance, 71, 161-176.

Lerner, J., & Wulf, J. (2007). Innovation and incentives: Evidence from corporate R&D. the Review of Economics and Statistics, 89, 634-644.

Levinthal, D. A., & March, J. G. (1993). The myopia of learning. Strategic management journal, 14, 95-112.

Lewellen, J. (2002). Momentum and autocorrelation in stock returns. The Review of Financial Studies, 15, 533-564.

Li, M., Lu, Y., & Phillips, G. M. (2019). CEOs and the product market: when are powerful CEOs beneficial? Journal of Financial and Quantitative Analysis, 54, 2295-2326.

Lim, B. Y., Wang, J. G., & Yao, Y. (2018). Time-series momentum in nearly 100 years of stock returns. Journal of Banking & Finance, 97, 283-296.

Lonare, G., Nart, A., & Tuncez, A. M. (2020). Industry Tournament Incentives and Corporate Hedging Policies. Available at SSRN 3397444.

Lutzenberger, F. T. (2014). The predictability of aggregate returns on commodity futures. Review of Financial Economics, 23, 120-130.

Manso, G. (2011). Motivating innovation. The Journal of Finance, 66, 1823-1860.

Mao, C. X., & Zhang, C. (2018). Managerial risk-taking incentive and firm innovation: Evidence from FAS 123R. Journal of Financial and Quantitative Analysis, 53, 867-898.

March, J. G. (1991). Exploration and exploitation in organizational learning. Organization science, 2, 71-87.

Marinovic, I., & Varas, F. (2019). CEO Horizon, Optimal Pay Duration, and the Escalation of Short-Termism. The Journal of Finance, 74, 2011-2053.

Mensi, W., Hammoudeh, S., Nguyen, D. K., & Yoon, S.-M. (2014). Dynamic spillovers among major energy and cereal commodity prices. Energy Economics, 43, 225-243.

Merton, R. C. (1973). Theory of rational option pricing. The Bell Journal of economics and management science, 141-183.

Miao, H., Ramchander, S., Wang, T., & Yang, D. (2017). Influential factors in crude oil price forecasting. Energy Economics, 68, 77-88.

Miffre, J. (2016). Long-short commodity investing: A review of the literature. Journal of Commodity Markets, 1, 3-13.

Miffre, J., & Rallis, G. (2007). Momentum strategies in commodity futures markets. Journal of Banking & Finance, 31, 1863-1886.

Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time series momentum. Journal of Financial Economics, 104, 228-250.

Mukherjee, A., Singh, M., & Žaldokas, A. (2017). Do corporate taxes hinder innovation? Journal of Financial Economics, 124, 195-221.

Narayan, P. K., Ahmed, H. A., & Narayan, S. (2015). Do momentum-based trading strategies work in the commodity futures markets? Journal of Futures Markets, 35, 868-891.

Narayanan, M. (1985). Managerial incentives for short-term results. The Journal of Finance, 40, 1469-1484.

Nazlioglu, S., & Soytas, U. (2011). World oil prices and agricultural commodity prices: Evidence from an emerging market. Energy Economics, 33, 488-496.

Ohashi, K., & Okimoto, T. (2016). Increasing trends in the excess comovement of commodity prices. Journal of Commodity Markets, 1, 48-64.

Paschke, R., Prokopczuk, M., & Simen, C. W. (2020). Curve momentum. Journal of Banking & Finance, 113, 1-18.

Pástor, L., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. Journal of Political Economy, 111, 642-685.

Pitkäjärvi, A., Suominen, M., & Vaittinen, L. (2020). Cross-asset signals and time series momentum. Journal of Financial Economics, 136, 63-85.

Rajgopal, S., & Shevlin, T. (2002). Empirical evidence on the relation between stock option compensation and risk taking. Journal of Accounting and Economics, 33, 145-171.

Rapach, D. E., Strauss, J. K., & Zhou, G. (2013). International stock return predictability: what is the role of the United States? The Journal of Finance, 68, 1633-1662.

Rapach, D. E., Strauss, J. K., Tu, J., & Zhou, G. (2019). Industry Return Predictability: A Machine Learning Approach. The Journal of Financial Data Science, 1, 9-28.

Reboredo, J. C. (2012). Do food and oil prices co-move? Energy policy, 49, 456-467.

Sagi, J. S., & Seasholes, M. S. (2007). Firm-specific attributes and the cross-section of momentum. Journal of Financial Economics, 84, 389-434.

Sakkas, A., & Tessaromatis, N. (2020). Factor based commodity investing. Journal of Banking & Finance, 105807.

Shanken, J. (1992). On the estimation of beta-pricing models. The Review of Financial studies, 5, 1-33.

Shen, C. H.-h., & Zhang, H. (2018). Tournament incentives and firm innovation. Review of Finance, 22, 1515-1548.

Shen, Q., Szakmary, A. C., & Sharma, S. C. (2007). An examination of momentum strategies in commodity futures markets. Journal of Futures Markets: Futures, Options, and Other Derivative Products, 27, 227-256.

Smith, C. W., & Stulz, R. M. (1985). The determinants of firms' hedging policies. Journal of financial and quantitative analysis, 391-405.

Soete, L. L. (1981). A general test of technological gap trade theory. Weltwirtschaftliches Archiv, 117, 638-660.

Stein, J. C. (1988). Takeover threats and managerial myopia. Journal of political economy, 96, 61-80.

Stein, J. C. (1989). Efficient capital markets, inefficient firms: A model of myopic corporate behavior. The quarterly journal of economics, 104, 655-669.

Szakmary, A. C., Shen, Q., & Sharma, S. C. (2010). Trend-following trading strategies in commodity futures: A re-examination. Journal of Banking & Finance, 34, 409-426.

Szymanowska, M., De Roon, F., Nijman, T., & Van Den Goorbergh, R. (2014). An anatomy of commodity futures risk premia. The Journal of Finance, 69, 453-482.

Tan, Y. (2020). Industry tournament incentives and audit fees. Journal of Business Finance & Accounting.

Tang, K., & Xiong, W. (2012). Index investment and the financialization of commodities. Financial Analysts Journal, 68, 54-74.

Tian, X., & Wang, T. Y. (2014). Tolerance for failure and corporate innovation. The Review of Financial Studies, 27, 211-255.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. Journal of the Royal Statistical Society: Series B (Methodological), 58, 267-288.

Wang, C. (2001). Investor sentiment and return predictability in agricultural futures markets. Journal of Futures Markets: Futures, Options, and Other Derivative Products, 21, 929-952.

Wang, Y., Wu, C., & Yang, L. (2014). Oil price shocks and agricultural commodity prices. Energy Economics, 44, 22-35.

Yang, Y. (2005). Can the strengths of AIC and BIC be shared? A conflict between model indentification and regression estimation. Biometrika, 92, 937-950.

You, L., & Daigler, R. T. (2013). AM arkowitz optimization of commodity futures portfolios. Journal of Futures Markets, 33, 343-368.

Zhang, Y., Ma, F., & Wang, Y. (2019). Forecasting crude oil prices with a large set of predictors: Can LASSO select powerful predictors? Journal of Empirical Finance, 54, 97-117.

Zhu, Y., & Zhou, G. (2009). Technical analysis: An asset allocation perspective on the use of moving averages. Journal of Financial Economics, 92, 519-544.

Zou, H. (2006). The adaptive lasso and its oracle properties. Journal of the American statistical association, 101, 1418-1429.

Zwiebel, J. (1995). Corporate conservatism and relative compensation. Journal of Political economy, 103, 1-25.

TABLES

TABLES FOR CHAPTER I

Table 1 Summary statistics for the commodity futures returns

Ticker	Name	Sector	Nobs	Mean	Median	Std.Dev	Skewness	Kurtosis	Tstat
BO	Soybean Oil	Grains	192	-0.57	-7.52	24.98	-0.08	4.88	-0.09
C	Corn	Grains	192	-3.3	-10.51	28.78	0.30	3.76	-0.46
KW	Kansas Wheat	Grains	192	-4.67	-10.32	30.56	0.51	4.32	-0.61
O	Oats	Grains	192	1.59	2.66	31.19	0.41	3.98	0.20
RR	Rough Rice	Grains	192	-5.79	-4.27	24.09	-0.02	3.56	-0.96
S	Soybean	Grains	192	5.44	1.48	25.84	-0.22	3.59	0.84
SM	Soybean Meal	Grains	192	11.84	6.87	29.30	0.28	3.83	1.62
W	Wheat	Grains	192	-6.86	-12.02	31.37	0.51	4.56	-0.87
CC	Cocoa	Softs	192	3.02	5.49	27.38	-0.02	2.81	0.44
CT	Cotton	Softs	192	-2.9	2.33	27.56	0.10	3.80	-0.42
DA	Milk	Softs	192	9.24	3.81	24.95	0.77	6.90	1.48
JO	Orange Juice	Softs	192	2.05	-2.99	31.13	0.10	2.93	0.26
KC	Coffee	Softs	192	-2.59	-20.58	30.12	1.03	5.69	-0.34
LB	Lumber	Softs	192	-11.17	-25.26	28.59	0.13	3.35	-1.56
SB	Sugar	Softs	192	3.31	-8.28	29.93	0.44	3.64	0.44
CL	Crude Oil	Energy	192	2.67	5.48	29.98	-0.37	3.64	0.36
HO	Heating Oil	Energy	192	4.33	5.26	28.44	-0.25	3.47	0.61
NG	Natural Gas	Energy	192	-21.89^{**}	-20.42	37.91	0.16	4.36	-2.31
HU/XB	Gasoline	Energy	192	9.83	17.47	34.09	0.24	6.89	1.15
FC	Feeder Cattle	Livestocks	192	2.16	2.07	16.24	0.11	3.43	0.53
LC	Live Cattle	Livestocks	192	0.37	0.55	13.97	-0.10	3.29	0.10
LH	Lean Hogs	Livestocks	192	-8.27	-6.95	25.25	0.17	3.40	-1.31
GC	Gold	Metal	192	7.59^{*}	4.74	17.40	-0.11	3.70	1.74
HG	Copper	Metal	192	9.77	5.91	26.68	-0.25	6.53	1.46
PA	Palladium	Metal	192	17.79^{**}	24.50	31.91	0.01	6.08	2.23
PL	Platinum	Metal	192	2.84	5.76	22.92	-0.64	6.13	0.50
SI	Silver	Metal	192	9.64	3.69	31.81	0.03	3.46	1.21

Table 2 LASSO predictive regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Regressor	Regressand								
	Cocoa	Coffee	Copper	Corn	Cotton	Crude Oil	Gasoline	Heating Oil	Kansas Wheat
(Intercept)	0	-0.01	0.01	0	0	0	0	0	-0.01
Cocoa1	-0.19***	-	-	-	-	-	-	-	-
Coffee1	-0.15**	-	-	-	-	-	-	-	-
Coffee2	0.19***	-	-	0.11	-	-	-	-	-
Copper1	-0.14	-	0.16**	-	-	-	-	-	-
Copper2	-	-	-	-	-	0.16	0.2**	0.19*	-
Cotton1	-0.05	-	-	-	-	-	-	-	-
Cotton2	-	-	-	0.12	0.07	-	-	-	0.2***
Crude Oil1	-	-	-	-	-	0.17**	-	0.11	-
Crude Oil2	-	-	-	-	-	-	-	-	-
Feeder Cattle2	-	-	-	-	-	-	-0.32***	-	-
Gasoline2	-0.05	-	-	-0.14**	-	-	-	-	-
Gold2	-	-	-	-	-	-	-	-	-
Heating Oil2	-	-	-	-	-	-	-	-	-
Kansas Wheat2	-0.06	-	-	-	-	-	-	-	-
Lean Hogs1	-	-	-	0.19**	0.14*	-	-	-	0.19**
Lumber1	0.13**	-	-	-	0.18***	-	-	-	-
Lumber2	-0.12**	-	-	-	-	-	-	-	-
Milk1	-	0.17	-	0.2***	-	-	-	-	0.18**
Milk2	-	0.27***	-	-	-	-	0.18**	-	-
Natural Gas1	0.09***	-	-	-	-	-	-	-	-
Oats2	-0.11*	-	-	-	-	-	-	-	-
Orange Juice1	-0.08**	-	-	-	-	-	-	-	-0.12**
Orange Juice2	-0.07	-	-	-	-	-	-	-	-
Palladium2	0.19***	-	-	-	0.03	-	0.07	-	-
Platinum1	0.27**	-	-	-	-	-	-	-	-
Platinum2	-	-	0.28***	-	-	0.21	0.21	0.16	-
Rough Rice1	-0.17***	-	-	-	-	-	-	-	-0.16
Rough Rice2	-	-	-	-	-	-	-	-	-0.25***
Soybean1	-	-	-	-	-	-	0.13	-	-
Soybean Meal1	0.22***	-	-	-	-	-	-	-	-
Soybean Oil1	-0.15**	-	-	-	-	-	0.15	0.15	-
Soybean Oil2	-	-	-	-	0.08	-	-	-	-
Sugar1	-	-	-	-	0.1	-	-	-	-
Sugar2	-	-	-	-	0.1	-	-	-	-
Wheat1	-	-	-	-	-	-	-	-	-
Adj R^2	24.01%	6.86%	8.37%	10.02%	8.17%	9.71%	16.07%	10.83%	11.64%

Table 2, continued

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Regressor	Regressand								
	Lean Hogs	Live Cattle	Lumber	Orange Juice	Soybean	Soybean Meal	Soybean Oil	Sugar	Wheat
(Intercept)	-0.01	0	-0.01	0	0.01	0.01***	0	0	0
Cocoa1	-	-	-	-	-	-	-	-	-
Coffee1	-	-	-	-	-	-	-	-	-
Coffee2	-	-	-	-	-	-	-	-	-
Copper1	-	-	-	-	-	-	-	-	-
Copper2	-	-	0.17*	-	-	-	-	-	-
Cotton1	-	-	-	-	-0.11	-	-	-	-
Cotton2	-	-	-	-	0.08	0.08	-	-	-
Crude Oil1	-	-	-	-	-	-	-	-	-
Crude Oil2	-	-	-	0.22***	-	-	-	-	-
Feeder Cattle2	-	-	-	-	-0.23**	-	-0.23**	-	-
Gasoline2	-	-	-	-	-	-	-	-	-
Gold2	-	-	-	-	-0.28***	-0.33**	-	-	-
Heating Oil2	0.14	-	-	-	-	-	-	-	-
Kansas Wheat2	-	-	-	-	-	-	-	-	-
Lean Hogs1	-	-	0.18**	-	0.14**	0.21***	-	-	0.3***
Lumber1	-	-	-	-	-	-	-	-	-
Lumber2	-	-	-	-	-	-	-	-	-
Milk1	-	-	-	-	0.1	-	0.2***	-	-
Milk2	0.13	-	-	-	-	-	-	-	-
Natural Gas1	0.08**	0.08***	-	-	-	-	-	-	-
Oats2	-	-	-	-	-	-	-	-	-
Orange Juice1	-	-	-	-	-	-	-	0.12*	-
Orange Juice2	-	-	-	-	-	-	-	-	-
Palladium2	-	-	-	-	-	-	-	0.16***	-
Platinum1	-	-	-	-	-	-	-	-	-
Platinum2	-	-	-	-	-	-	-	-	-
Rough Rice1	-	-	-	-	-	-	-	-	-
Rough Rice2	-	-	-	-	-	-	-	-	-
Soybean1	-	-	-	-	-	-	-0.12	-	-
Soybean Meal1	-	-	-	-	-	-	-	0.1	-
Soybean Oil1	-	-	-	-	-	-	-	-	-
Soybean Oil2	-	-	-	-	0.16**	0.16	0.17***	-	-
Sugar1	-	-	-	-	-	-	-	0.18***	-
Sugar2	-	-	-	-	-	-	-	-	-
Wheat1	-0.15***	-	-	-	-	-	-	-	-
Adj R^2	7.49%	4.96%	4.47%	4.01%	10.09%	7.07%	8.99%	8.47%	5.18%

Table 3 Performance of the single-sort portfolios

Forecasts	Ann. mean (%)	Ann. std (%)	Ann. Sharpe Ratio	Ann. DR (%)	Ann. Sortino Ratio (%)	Tstat
Prevailing mean	1.78	17.56	0.10	12.10	0.15	0.34
OLS	-4.22	20.40	-0.21	14.91	-0.28	-0.69
LASSO	15.15	16.24	0.93	8.28	1.83	3.09
LASSO (All)	14.67	17.17	0.85	8.61	1.70	2.83

Table 4 Abnormal alphas for the single-sort portfolios

Variables	Prevailing mean	OLS	LASSO	LASSO (All)
$\alpha(\%)$	-0.082	-0.213	1.384***	1.216**
	(-0.252)	(-0.417)	(2.736)	(2.313)
Average	34.132***	5.535	17.196	22.258
	(3.562)	(0.261)	(1.014)	(1.587)
Basis	-1.098	-2.619	-1.291	-1.118
	(-0.121)	(-0.232)	(-0.153)	(-0.103)
HP	31.459***	-10.899	-13.664	1.014
	(4.126)	(-0.964)	(-1.209)	(0.091)
Momentum	32.394***	19.628*	4.274	6.164
	(3.414)	(1.755)	(0.472)	(0.74)
Adj R^2	35.28%	-0.49%	-0.06%	-0.21%

Table 5 Performance of the timing portfolios

Forecasts	Ann. mean (%)	Ann. std (%)	Ann. Sharpe Ratio	Ann. DR (%)	Ann. Sortino Ratio (%)	Tstat	Ann.alpha (%)	Alpha.tstat
Prevailing mean	1.80	7.32	0.25	5.29	0.34	0.82	1.53	(1.13)
OLS	0.12	7.18	0.02	5.04	0.02	0.06	0.87	(0.43)
LASSO	6.15	8.52	0.72	5.30	1.16	2.40	7.26***	(3.11)
LASSO (All)	3.53	6.64	0.53	4.31	0.82	1.76	4.13***	(2.66)

Table 6 Performance of other benchmarks

Forecasts	Ann. mean (%)	Ann. std (%)	Ann. Sharpe Ratio	Ann. DR (%)	Ann. Sortino Ratio (%)	Tstat	Ann.alpha (%)	Alpha.tstat
Panel A: Single-sort portfolio								
AR1	11.20	18.02	0.62	10.24	1.09	2.06	8.98*	(1.71)
AR2	11.14	18.75	0.59	10.96	1.02	1.97	9.17*	(1.82)
AR3	9.77	16.81	0.58	9.71	1.01	1.93	7.92	(1.45)
Basis	9.01	17.96	0.50	11.70	0.77	1.66	7.14	(1.55)
Momentum	5.27	15.22	0.35	9.80	0.54	1.15	4.73	(1.32)
Basis and momentum	7.87	16.26	0.48	9.84	0.80	1.61	6.94	(1.60)
Hedging pressure	11.23	17.06	0.66	10.13	1.11	2.18	10.95**	(2.55)
Basis, momentum, and hedging pressure	7.73	16.56	0.47	11.19	0.69	1.55	7.74	(1.48)
Panel B: Timing portfolio								
AR1	2.61	6.39	0.41	4.41	0.59	1.36	2.189	(1.25)
AR2	2.86	6.50	0.44	3.95	0.72	1.46	2.136	(1.25)
AR3	1.71	6.00	0.28	3.69	0.46	0.94	0.828	(0.48)
Basis	2.92	6.96	0.42	4.84	0.60	1.39	2.771**	(1.98)
Momentum	-0.01	6.51	0.00	4.73	0.00	-0.01	0.002	(0.00)
Basis and momentum	1.19	6.62	0.18	4.79	0.25	0.60	0.917	(0.47)
Hedging pressure	0.94	6.03	0.16	4.05	0.23	0.52	1.176	(0.75)
Basis, momentum, and hedging pressure	0.79	5.80	0.14	4.07	0.19	0.45	0.832	(0.45)

Table 7 Out-of-sample portfolio performance using indexed futures only

Forecasts	Ann. mean (%)	Ann. std (%)	Ann. Sharpe Ratio	Ann. DR (%)	Ann. Sortino Ratio (%)	Tstat	Ann.alpha (%)	Alpha.tstat
Panel A: Single-sort portfolio								
Prevailing mean	4.14	17.54	0.24	11.88	0.35	0.78	-0.33	(-0.07)
OLS	10.90	20.33	0.54	11.59	0.94	1.78	10.75	(1.57)
LASSO	13.00	18.69	0.70	10.54	1.23	2.31	13.26**	(2.33)
LASSO (All)	11.48	17.87	0.64	10.26	1.12	2.13	10.04	(1.64)
Panel B: Timing portfolio								
Prevailing mean	2.12	9.55	0.22	6.76	0.31	0.74	1.38	(0.56)
OLS	1.26	10.04	0.13	6.83	0.18	0.41	2.71	(0.91)
LASSO	8.62	12.43	0.69	7.46	1.16	2.30	9.90**	(2.34)
LASSO (All)	6.93	9.40	0.74	4.90	1.41	2.44	7.68**	(2.45)

Table 8 Out-of-sample portfolio performance using non-indexed futures only

Forecasts	Ann. mean (%)	Ann. std (%)	Ann. Sharpe Ratio	Ann. DR (%)	Ann. Sortino Ratio (%)	Tstat	Ann.alpha (%)	Alpha.tstat
Panel A: Single-sort portfolio								
Prevailing mean	1.70	17.38	0.10	11.42	0.15	0.32	1.42	(0.29)
OLS	-0.97	19.94	-0.05	14.62	-0.07	-0.16	-1.38	(-0.21)
LASSO	4.02	30.06	0.13	19.85	0.20	0.44	2.18	(0.29)
LASSO (All)	0.37	18.35	0.02	13.10	0.03	0.07	-1.27	(-0.27)
Panel B: Timing portfolio								
Prevailing mean	1.60	9.79	0.16	6.62	0.24	0.54	2.32	(1.00)
OLS	3.40	11.01	0.31	7.49	0.45	1.02	3.75	(1.02)
LASSO	-0.91	16.15	-0.06	11.14	-0.08	-0.19	-0.08	(-0.02)
LASSO (All)	1.03	10.15	0.10	6.90	0.15	0.34	1.541	(0.50)

Table 9 LASSO predictive regression with interactions of ETF inception dummy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Regressand						
Regressor	Coffee	Copper	Corn	Cotton	Crude Oil	Gasoline	Heating Oil
(Intercept)	0	0.04^{***}	0	0	0	0	0
d_ETF	-	-0.04^{***}	-	-	-	-	-
Cocoa1	-	-	-	-	-	-	-
Cocoa2	-	-	-	-	-	-	-
Cocoa2*d_ETF	-	-	-	-	-	-	-
Coffee1	-	-	-	-	-	-	-
Coffee1*d_ETF	-	-	-	0.07	-	-	-
Coffee2	-	-	-	-	-	-	-
Coffee2*d_ETF	-	-	0.1	-	-	-	-
Copper1	-	0.05	-	-	-	-	-
Copper2	-	-	-	-	0.15	0.22^{**}	0.18^{*}
Corn2*d_ETF	-	-	-	-	0.15^{**}	-	0.13
Cotton1	-	-	-	-	-	-	-
Cotton1*d_ETF	-	-	-0.18	-	-	-	-
Cotton2	-	-	-	-	-	-	-
Cotton2*d_ETF	-	-	0.16	-	-	-	-
Crude Oil2	-	-	-	-	-	-	-
Feeder Cattle1*d_ETF	-	0.29^{**}	-	-	-	-	-
Feeder Cattle2	-	-	-	-	-	-	-
Gasoline1	-	-	-	-	-	-	-
Gasoline1*d_ETF	-	0.09	-	-	0.2^{**}	-	0.11
Gasoline2	-	-	-0.17^{***}	-	-	-	-
Gold2	-	-	-	-	-	-	-
Heating Oil2	-	-	-	-	-	-	-
Heating Oil2*d_ETF	-	-	-	-	-	-	-
Kansas Wheat2	-	-	-	-	-	-	-
Lean Hogs1	-	-	-	0.12	-	-	-
Lean Hogs1*d_ETF	-	-	0.24^{***}	-	-	-	-
Lean Hogs2*d_ETF	-	-	-	-	-	-	-
Live Cattle2*d_ETF	-	-	-	0.25	-	-	-
Lumber1	-	-	-	0.16^{***}	-	-	-
Lumber2	-	-	-	-	-	-	-
Lumber2*d_ETF	-	-	-	-	-	-	-
Milk1	-	-	0.05	-	-	-	-
Milk1*d_ETF	-	-	0.2	-	-	-	-
Milk2	0.29^{***}	-	-	-	-	0.17^{**}	-
Milk2*d_ETF	-	-	0.2^{*}	0.13	-	-	-
Natural Gas1	-	-	-	-	-	-	-
Oats2	-	-	-	-	-	-	-
Orange Juice1	-	-	-	-	-	-	-
Orange Juice1*d_ETF	-	-	-	-	-	-	-
Orange Juice2	-	-	-	-	-	-	-
Palladium2	-	0.06	-	-	-	-	-
Palladium2*d_ETF	-	-	-	0.12^{**}	-	-	-
Platinum1	-	-	-	-	-	-	-
Platinum2	-	0.22	-	-	0.16	0.26^{**}	0.12
Rough Rice1	-	-	-	-	-	-	-
Rough Rice1*d_ETF	-	-	-	-	-	-	-
Rough Rice2*d_ETF	-	-	-	-	-	-	-
Soybean1	-	-	-	-	-	0.12	-
Soybean Meal1	-	-	-	-	-	-	-
Soybean Oil1	-	-	-	-	-	0.15	0.13
Soybean Oil2	-	-	0.11	-	-	-	-
Sugar1	-	-	-	0.08	-	-	-
Sugar2*d_ETF	-	-	-	0.16^{**}	-	-	-
Wheat1	-	-	-	-	-	-	-
Total number of interactions	0	3	6	5	2	0	2
Fstat	-	4.912^{***}	4.606^{***}	3.827^{***}	5.346^{***}	-	2.562^{*}
Adj R^2	5.30%	13.66%	15.76%	12.34%	11.51%	14.35%	11.62%

Table 9, continued

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Regressand						
Regressor	Kansas Wheat	Lean Hogs	Live Cattle	Natural Gas	Soybean	Sugar	Wheat
(Intercept)	-0.01	-0.01*	0	-0.02**	0.01	0	-0.01
d_ETF	-	-	-	-	-	-	-
Cocoa1	-	-	-	-	-	-	-
Cocoa2	-	-	-	-	-0.12	-	-
Cocoa2*d_ETF	-0.13	-	-	-	-	-	-
Coffee1	-	-	-	-	-	-	-
Coffee1*d_ETF	-	-	-	-	-	-	-
Coffee2	-	-	-	-	-	-	-
Coffee2*d_ETF	-	-	-	-	-	-	-
Copper1	-	-	-	-	-	-	-
Copper2	-	-	-	-	-	-	-
Corn2*d_ETF	-	-	-	-	-	-	-
Cotton1	-	-	-	-	-	-	-
Cotton1*d_ETF	-0.1	-	-	-	-0.24***	-	-0.12
Cotton2	-	-	-	-	0.03	-	-
Cotton2*d_ETF	0.36***	-	-	-	0.1	-	0.34***
Crude Oil2	-	-	-	-	-	-	-
Feeder Cattle1*d_ETF	-	-	-	-	-	-	-
Feeder Cattle2	-	-	-	-	-0.28***	-	-
Gasoline1	0.08	-	-	0.13	-	-	-
Gasoline1*d_ETF	-	-	-	-	-	-	-
Gasoline2	-	-	-	-	-	-	-0.09
Gold2	-	-	-	-	-0.27***	-	-
Heating Oil2	-	0.17**	-	-	-	-	-
Heating Oil2*d_ETF	-	-	-	0.18	-	-	-
Kansas Wheat2	-	-	-	-	-	-	-
Lean Hogs1	-	-	-	-	-	-	0.11
Lean Hogs1*d_ETF	0.2**	-	-	-	0.15**	-	0.12
Lean Hogs2*d_ETF	0.13	-	-	-	-	-	-
Live Cattle2*d_ETF	-	-	-	-	-	-	-
Lumber1	-	-	-	-	-	-	-
Lumber2	-	-	-	-	-	-	-
Lumber2*d_ETF	-0.12	-	-	-	-	-	-0.15
Milk1	0.02	-	-	-	0.09	-	-
Milk1*d_ETF	0.16	-	-	-	-	-	0.16
Milk2	-	-	-	-	-	-	-
Milk2*d_ETF	0.27***	-	-	-	0.22***	-	0.27**
Natural Gas1	-	-	0.08***	-	-	-	-
Oats2	-	-	-	-	-	-	-
Orange Juice1	-0.11**	-	-	-	-	-	-0.1*
Orange Juice1*d_ETF	-	-	-	-	-	0.15**	-
Orange Juice2	-	-	-	-	-	-	-
Palladium2	-	-	-	-	-	0.16***	-
Palladium2*d_ETF	-0.13	-	-	-	-	-	-
Platinum1	-	-	-	-	0.16	-	-
Platinum2	-	-	-	-	-	-	-0.14
Rough Rice1	-	-	-	-	-	-	-0.02
Rough Rice1*d_ETF	-0.22**	-	-	-	-	-	-0.14
Rough Rice2*d_ETF	-0.23***	-	-	0.28**	-	-	-0.31***
Soybean1	-	-	-	-	-	-	-
Soybean Meal1	-	-	-	-	-	0.1	-
Soybean Oil1	-	-	-	-	-	-	-
Soybean Oil2	-	-	-	-	0.17**	-	-
Sugar1	-	-	-	-	-	0.18***	-

Sugar2*d_ETF	-	-	-	-	-	-	-
Wheat1	-	-0.13^{***}	-	-	-	-	-
Total number of interactions	11	0	0	2	4	1	8
Fstat	4.606^{***}	-	-	4.323^{**}	5.364^{***}	4.04^{**}	4.097^{***}
Adj R^2	20.18%	5.50%	4.96%	4.76%	16.62%	8.97%	18.96%

Table 10 LASSO portfolios with different model specifications

Trading Strategies	Forecasts	Ann. mean (%)	Ann. std (%)	Ann. Sharpe Ratio	Ann. DR (%)	Ann. Sortino Ratio (%)	Tstat	Ann.alpha (%)	Alpha.tstat
Single-sort portfolio	**Panel A1: Adaptive LASSO**								
	LASSO	15.24	16.32	0.93	8.66	1.76	3.10	16.45***	(2.92)
	LASSO (All)	14.80	17.10	0.87	8.49	1.74	2.87	14.88**	(2.48)
	Panel B1: Elastic net with a blending parameter of 0.5								
	LASSO	11.21	15.63	0.72	8.42	1.33	2.38	12.41*	(1.91)
	LASSO (All)	6.69	18.31	0.37	11.11	0.60	1.21	5.32	(1.01)
	Panel C1: C-LASSO								
	LASSO	14.56	17.07	0.85	9.76	1.49	2.83	14.86***	(2.86)
	LASSO (All)	15.05	16.62	0.91	9.21	1.63	3.00	15.61***	(3.16)
	Panel D1: Adjusting for seasonality								
	LASSO	14.02	17.28	0.81	9.76	1.44	2.69	14.66***	(2.79)
	LASSO (All)	17.04	15.63	1.09	7.96	2.14	3.61	16.75***	(3.48)
	Panel E1: 3 lags								
	LASSO	12.14	17.41	0.7	10.88	1.12	2.31	12.95**	(2.35)
	LASSO (All)	13.03	17.35	0.75	10.6	1.23	2.49	13.97***	(2.66)
Timing portfolio	**Panel A2: Adaptive LASSO**								
	LASSO	5.85	8.55	0.68	5.37	1.09	2.27	6.69***	(2.80)
	LASSO (All)	3.41	6.71	0.51	4.41	0.77	1.68	3.85**	(2.56)
	Panel B2: Elastic net with a blending parameter of 0.5								
	LASSO	6.82	10.09	0.68	6.68	1.02	2.24	6.97***	(2.66)
	LASSO (All)	2.33	7.34	0.32	5.02	0.46	1.05	2.25	(1.41)
	Panel C2: C-LASSO								
	LASSO	3.76	7.30	0.52	4.34	0.87	1.71	3.64*	(1.70)
	LASSO (All)	3.80	7.09	0.54	4.08	0.93	1.78	3.79*	(1.91)
	Panel D2: Adjusting for seasonality								
	LASSO	7.31	7.66	0.95	4.19	1.75	3.16	8.13***	(4.05)
	LASSO (All)	4.59	6.53	0.7	3.73	1.23	2.33	4.98***	(2.88)
	Panel E2: 3 lags								
	LASSO	6.36	7.14	0.89	3.69	1.72	2.96	6.59***	(3.64)
	LASSO (All)	5.54	6.59	0.84	3.25	1.7	2.79	5.67***	(3.48)

Table 11 Tree-based models

Forecasts	Ann. mean (%)	Ann. std (%)	Ann. Sharpe Ratio	Ann. DR (%)	Ann. Sortino Ratio (%)	Tstat	Ann.alpha	Alpha.tstat
Panel A: Single-sort portfolio								
Gradient boosting	12.54	17.56	0.71	10.77	1.16	2.37	11.41*	(1.96)
Random forest	13.58	17.19	0.79	10.08	1.35	2.62	11.15**	(2.43)
Panel B: Timing portfolio								
Gradient boosting	3.21	7.99	0.40	5.59	0.57	1.33	3.79	(1.64)
Random forest	2.67	7.90	0.34	5.34	0.50	1.12	2.08	(0.88)

Table 12 Neural networks with one hidden layer

Forecasts	Ann. mean (%)	Ann. std (%)	Ann. Sharpe Ratio	Ann. DR (%)	Ann. Sortino Ratio (%)	Tstat	Ann.alpha	Alpha.tstat
Panel A: Single-sort portfolio								
4 neurons	5.20	18.01	0.29	11.17	0.47	0.96	6.816*	(1.83)
8 neurons	2.55	19.20	0.13	12.82	0.20	0.44	3.755	(0.79)
32 neurons	7.12	18.38	0.39	12.10	0.59	1.29	7.655	(1.51)
Panel B: Timing portfolio								
4 neurons	0.40	8.36	0.05	6.21	0.06	0.16	0.727	(0.29)
8 neurons	1.10	7.17	0.15	4.92	0.22	0.51	1.832	(0.80)
32 neurons	1.29	10.74	0.12	7.75	0.17	0.40	1.973	(0.65)

TABLES FOR CHAPTER II

Table 13 Summary statistics of factors

	Count	Mean (%)	Std (%)	Sharpe Ratio	Skew	Kurtosis	Min (%)	Max (%)
Trend	192	13.48*** (2.6)	20.70	0.65	-0.03	0.29	-164.71	234.09
MOM	192	2.06 (0.38)	21.51	0.10	0.07	0.33	-191.48	216.94
BASIS	192	7.29 (1.63)	17.93	0.41	0.33	0.14	-155.73	186.20
HP	192	9.01* (1.76)	20.53	0.44	0.33	0.29	-156.13	250.43
AVG	192	2.19 (0.64)	13.66	0.16	-0.44	3.15	-208.99	160.85
BASIS-MOM	192	10.52** (2.04)	20.66	0.51	-0.15	0.18	-207.64	180.40
Value	192	5.39 (1.01)	21.43	0.25	-0.08	0.56	-224.49	203.99

Table 14 Factor summary statistics: Recession (financial crisis) and expansion periods

Factor	Count	Mean (%)	Std (%)	Sharpe Ratio	Skew	Kurtosis	Min (%)	Max (%)
	Panel A: Financial crisis period (Dec 2007-June 2009)							
Trend	18	35.05* (1.83)	23.43	1.50	-0.58	0.64	-138.20	184.24
MOM	18	-14.36 (-0.61)	28.62	-0.50	0.78	1.19	-165.77	216.94
BASIS	18	30.81 (1.59)	23.79	1.29	0.48	-0.67	-94.24	186.20
HP	18	31.04 (1.29)	29.37	1.06	0.67	0.30	-118.46	250.43
AVG	18	-15.33 (-0.67)	27.86	-0.55	-0.06	-0.11	-208.99	160.85
BASIS-MOM	18	-3.97 (-0.21)	22.76	-0.17	0.40	-0.38	-128.14	145.62
Value	18	-0.73 (-0.03)	27.37	-0.03	0.45	-0.27	-161.45	203.99
	Panel B: Expansion period							
Trend	174	11.25** (2.1)	20.36	0.55	0.01	0.38	-164.71	234.09
MOM	174	3.76 (0.69)	20.68	0.18	-0.03	0.18	-191.48	171.25
BASIS	174	4.86 (1.08)	17.15	0.28	0.19	0.05	-155.73	155.96
HP	174	6.73 (1.32)	19.38	0.35	0.10	-0.30	-156.13	170.49
AVG	174	4 (1.35)	11.26	0.35	-0.10	1.54	-157.23	128.59
BASIS-MOM	174	12.02** (2.24)	20.45	0.59	-0.21	0.34	-207.64	180.40
Value	174	6.03 (1.1)	20.81	0.29	-0.17	0.75	-224.49	203.43

Table 15 Extreme values and correlation matrix of factors

Factor	MDD(%)	Calma r(%)	n(ret <-0.1)	n(ret <-0.15)	n(ret <-0.2)	n(ret <-0.25)
Panel A: Extreme values						
Trend	42.29	31.87	10	0	0	0
MOM	63.37	3.26	13	1	0	0
BASIS	32.44	22.48	2	0	0	0
HP	36.88	24.44	5	0	0	0
AVG	43.72	5.00	3	1	0	0
BASIS-MOM	31.57	33.32	10	1	0	0
Value	71.17	7.58	9	2	0	0

Panel B: Correlation matrix							
	Trend	MOM	BASIS	HP	AVG	BASIS-MOM	Value
Trend	1.00	0.26	-0.16	0.12	0.07	-0.03	-0.13
MOM	0.26	1.00	0.26	0.41	0.06	0.10	-0.43
BASIS	-0.16	0.26	1.00	0.24	0.00	0.15	-0.24
HP	0.12	0.41	0.24	1.00	0.26	0.00	-0.25
AVG	0.07	0.06	0.00	0.26	1.00	-0.10	-0.23
BASIS-MOM	-0.03	0.10	0.15	0.00	-0.10	1.00	0.16
Value	-0.13	-0.43	-0.24	-0.25	-0.23	0.16	1.00

Table 16 Comparison of trend and momentum

Portfolio	Mean (%)	Std (%)	Skew	Kurtosis	Differ (%)	Corr
	Panel A: Full sample					
Trend long	8.65* (1.77)	19.56	0.06	1.28	4.58 (1.14)	0.65
Momentum long	4.07 (0.87)	18.64	-0.05	2.20		
Trend short	-4.83 (-1.07)	18.12	-0.03	1.50	-6.83** (-1.73)	0.63
Momentum short	2.01 (0.43)	18.82	0.50	1.43		
Trend	13.48*** (2.6)	20.70	-0.03	0.29	11.41** (1.77)	0.26
MOM	2.06 (0.38)	21.51	0.07	0.33		
	Panel B: Financial crisis period (Dec 2007-June 2009)					
Trend long	11.98 (0.43)	34.42	0.29	-0.16	37.24*** (2.96)	0.81
Momentum long	-25.26 (-0.96)	32.11	-0.08	0.65		
Trend short	-23.06 (-0.99)	28.68	-0.30	-0.32	-12.17 (-0.76)	0.74
Momentum short	-10.9 (-0.5)	26.93	1.44	4.59		
Trend	35.05* (1.83)	23.43	-0.58	0.64	49.41** (2.08)	0.45
MOM	-14.36 (-0.61)	28.62	0.78	1.19		
	Panel C: Expansion period					
Trend long	8.31* (1.81)	17.49	-0.15	0.69	1.21 (0.29)	0.57
Momentum long	7.1 (1.63)	16.56	0.40	1.15		
Trend short	-2.94 (-0.67)	16.69	0.27	1.51	-6.28* (-1.55)	0.60
Momentum short	3.34 (0.71)	17.84	0.29	0.34		
Trend	11.25** (2.1)	20.36	0.01	0.38	7.48 (1.13)	0.25
MOM	3.76 (0.69)	20.68	-0.03	0.18		

Table 17 Alphas and factor loadings

	Low	High	Trend (High-Low)
Panel A: Boons and Prado (2019)			
Alpha (%)	-0.57**	0.56*	1.12***
	(-2.94)	(2.12)	(3.13)
BASIS-MOM	0.97***	1.07***	0.11
	(-5.09)	(2.19)	(4.43)
AVG	-0.01	-0.04	-0.02
	(2.67)	(-3.16)	(-3.96)
Panel B: Bakshi et al. (2019)			
Alpha (%)	-0.62***	0.61**	1.23***
	(-2.94)	(2.12)	(3.13)
Momentum	-0.21***	0.09**	0.31***
	(-5.09)	(2.19)	(4.43)
BASIS	0.12***	-0.16***	-0.28***
	(2.67)	(-3.16)	(-3.96)
AVG	0.99***	1.07***	0.08
	(19.3)	(12.62)	(0.7)
Panel C: Sakkas and Tessaromatis (2020)			
Alpha (%)	-0.57**	0.67**	1.24***
	(-2.52)	(2.39)	(3.07)
MOM	-0.21***	0.06	0.27***
	(-4.39)	(1.2)	(3.82)
BASIS	0.13**	-0.17***	-0.3***
	(2.59)	(-3.16)	(-1.02)
HP	-0.05	0	0.05
	(-0.88)	(-0.09)	(0.52)
AVG	1***	1.04***	0.05
	(15.03)	(11.52)	(0.37)
BASIS-MOM	0	-0.01	-0.01
	(-0.05)	(-0.16)	(-0.08)
Value	-0.04	-0.09	-0.05
	(-0.88)	(-1.53)	(-0.61)

Table 18 GRS tests

Baseline model	GRS F statistics	pvalue
Boons and Prado (2019): BASIS-MOM, AVG	2.69	0.07
Bakshi et al. (2019): MOM, BASIS, AVG	2.17	0.09
Sakkas and Tessaromatis (2020): MOM, BASIS, AVG, HP, BASIS-MOM, Value	2.13	0.05

Table 19 Multivariate regression tests

	(1)	(2)	(3)	(4)
Panel A: Fama-MacBeth regressions				
ER_{trd}^{12}	0.41***	0.37***	0.38***	0.4***
	(3.9)	(3.59)	(3.18)	(3.04)
$R_{-1,-12}$			0	0
			(-0.23)	(-0.35)
$lnyt$			-0.06	0.01
			(-1.3)	(0.12)
HP_{it}				0.02***
				(2.86)
BASIS-MOM		0.06***		0.09***
		(3.47)		(3.58)
Value				0.01
				(1.13)
Panel B: Pooled OLS regression with commodity and time fixed effects				
Constant	-0.01	-0.01	-0.02*	-0.03***
	(-1.49)	(-1.5)	(-1.91)	(-2.64)
ER_{trd}^{12}	0.21*	0.22*	0.27**	0.28**
	(1.65)	(1.67)	(2.09)	(2.14)
$R_{-1,-12}$			-0.01*	-0.01
			(-1.79)	(-1.53)
$lnyt$			0.02	0.032
			(0.59)	(1.05)
HP_{it}				0.017
				(1.41)
BASIS-MOM		0.04**		0.047*
		(2.03)		(1.96)
Value				0.01*
				(1.84)

Table 20 Risk premiums (%)

	γ_{trend}	γ_{mom}	γ_{basis}	γ_{HP}	γ_{AVG}	$\gamma_{BASIS-MOM}$	γ_{Value}
Panel A: Constant betas							
Model 1	1.17***						
	(3.04)						
Model 2	1.3***				3.16	-0.41	
	(2.82)				(0.79)	(-0.28)	
Model 3	1.23***	0.72	-0.52		-0.72		
	(2.76)	(0.33)	(-0.15)		(-0.55)		
Model 4	1.52***	1.19	-2.73	-6.25	-4.22	-5.84	-10.37
	(1.11)	(0.22)	(-0.2)	(-0.31)	(-0.35)	(-0.21)	(-0.3)
Panel B: Rolling betas							
Model 1	1.05***						
	(2.73)						
Model 2	1.22***				-1.84	-1.09	
	(2.73)				(-1.36)	(-1.09)	
Model 3	1.18***	0.1	0.01		-1.6		
	(2.82)	(0.07)	(0)		(-1.44)		
Model 4	1.4	-0.02	-1.27	1.27	-4.66	4.61	-2.97
	(1.4)	(0)	(-0.21)	(0.19)	(-0.86)	(0.65)	(-0.42)

Table 21 What explained the trend factor?

Const	0.012***	0	0.01	0	0.01***	0.01**	0.01***	0.01***	0.01***	0.01***	0.01***	0.01**	0.01***	-0.009
	(2.96)	(-0.42)	(1.34)	(-0.25)	(2.88)	(2.59)	(2.81)	(2.78)	(2.8)	(2.73)	(2.78)	(2.42)	(2.61)	(-0.67)
IP	-0.73													-0.64
	(-1.31)													(-1.18)
Default		1.45*												-0.304
		(1.66)												(-0.21)
Term			0.1											0.488
			(0.27)											(1.21)
TED				2.22***										3.093***
				(2.79)										(2.85)
LIQ					-0.01									0.06
					(-0.11)									(0.73)
VIX						-0.01								-0.022
						(-0.39)								(-0.7)
MKT							0							0.001
							(0.01)							(0.57)
SMB								0						-0.003
								(-0.99)						(-1.17)
HML									0					0.001
									(-0.2)					(0.51)
UMD										0				0
										(-0.01)				(0.12)
RWM											0			-0.002
											(-0.2)			(-0.62)
CMA												0		-0.002
												(-0.25)		(-0.53)
Sent													0	
													(-0.3)	

Table 22 Comparison of trend and momentum, using active contracts

Portfolio	Mean (%)	Std (%)	Skew	Kurtosis	Differ%	Corr	Ann. Alpha (%)
	Panel A: Full sample						
Trend long	8.58*** (1.75)	19.64	0.01	1.18	4.57 (1.06)	0.60	6.92*** (2.77)
Momentum long	4.01*** (0.84)	19.00	-0.42	3.46			
Trend short	-7.4*** (-1.62)	18.28	0.27	2.03	-11*** (-2.62)	0.58	-8.62*** (-3.26)
Momentum short	3.6*** (0.79)	18.30	0.59	1.75			
Trend	15.98*** (3.06)	15.09	-0.30	0.93	15.58** (2.24)	0.23	15.54*** (3.89)
MOM	0.4 (0.08)	18.54	-0.60	2.75			
	Panel B: Financial crisis period (Dec 2007-June 2009)						
Trend long	3*** (0.12)	31.78	0.14	0.18	29.99** (2.09)	0.80	15.9 (1.62)
Momentum long	-26.99*** (-1.03)	32.20	-0.97	1.78			
Trend short	-21.96*** (-0.89)	30.28	0.02	-0.13	-9.2 (-0.45)	0.67	-22.5 (-1.5)
Momentum short	-12.76*** (-0.55)	28.65	1.45	3.87			
Trend	24.96 (1.22)	26.01	-0.12	-0.35	39.19* (1.41)	0.44	38.39 (1.61)
MOM	-14.23 (-0.55)	30.95	-0.90	1.75			
	Panel C: Expansion period						
Trend long	9.16*** (1.93)	18.06	0.00	0.90	1.94 (0.43)	0.53	5.91** (2.18)
Momentum long	7.21*** (1.62)	16.95	0.35	1.32			
Trend short	-5.89*** (-1.35)	16.63	0.56	2.23	-11.19*** (-2.7)	0.56	-9.26*** (-3.49)
Momentum short	5.3*** (1.19)	16.93	0.36	0.35			
Trend	15.05*** (2.8)	13.56	-0.21	0.39	13.13** (1.84)	0.10	15.18*** (3.62)
MOM	1.92 (0.36)	16.50	0.09	0.08			

Table 23 Comparison of trend and momentum, using the original settlement prices to calculate excess returns

Portfolio	Mean (%)	Std (%)	Skew	Kurtosis	Differ%	Corr	Ann. Alpha (%)
	Panel A: Full sample						
Trend long	8.65*** (1.77)	19.56	0.06	1.28	4.58 (1.14)	0.65	8.07** (2.39)
Momentum long	4.07*** (0.87)	18.64	-0.05	2.20			
Trend short	-4.83*** (-1.07)	18.12	-0.03	1.50	-6.83** (-1.73)	0.63	-6.78** (-2.52)
Momentum short	2.01*** (0.43)	18.82	0.50	1.43			
Trend	13.48*** (2.6)	18.37	-0.10	1.13	11.41** (1.77)	0.11	14.86*** (3.07)
MOM	2.06 (0.38)	15.81	-0.23	1.68			
	Panel B: Financial crisis period (Dec 2007-June 2009)						
Trend long	11.98*** (0.43)	34.42	0.29	-0.16	37.24*** (2.96)	0.81	26.07* (1.85)
Momentum long	-25.26*** (-0.96)	32.11	-0.08	0.65			
Trend short	-23.06*** (-0.99)	28.68	-0.30	-0.32	-12.17 (-0.76)	0.74	-9.34 (-0.93)
Momentum short	-10.9*** (-0.5)	26.93	1.44	4.59			
Trend	35.05* (1.83)	25.91	-0.12	0.11	49.41** (2.08)	0.45	35.42** (2.45)
MOM	-14.36 (-0.61)	27.86	-0.30	-0.44			
	Panel C: Expansion period						
Trend long	8.31*** (1.81)	17.49	-0.15	0.69	1.21 (0.29)	0.57	5.59 (1.6)
Momentum long	7.1*** (1.63)	16.56	0.40	1.15			
Trend short	-2.94*** (-0.67)	16.69	0.27	1.51	-6.28* (-1.55)	0.60	-6.82** (-2.47)
Momentum short	3.34*** (0.71)	17.84	0.29	0.34			
Trend	11.25** (2.1)	17.48	-0.03	1.24	7.48 (1.13)	0.25	12.41** (2.48)
MOM	3.76 (0.69)	13.92	0.31	0.83			

TABLES FOR CHAPTER III

Table 24 Descriptive statistics and correlations of firm variables

Panel A: Summary statistics

Variable	N	Mean	Std. dev.	25th pctl	Median	75th pctl
Dependent variables						
Prod_Innov$_{t+1}$	12,806	0.144	0.095	0.077	0.121	0.188
Prod_Announce$_{t+1}$	4,620	0.377	0.586	0.000	0.000	0.693
nPats$_{t+3}$	11,622	0.849	1.124	0.000	0.298	1.401
InnovEff$_{t+3}$	7,594	0.071	0.113	0.002	0.026	0.089
nCits$_{t+3}$	11,622	1.557	1.849	0.000	0.724	2.901
PatValue$_{t+3}$	10,083	0.096	0.146	0.000	0.024	0.144
Incentives variables						
Ind_Pay_Gap$_t$ (FF30) ($000)	12,806	25,159.903	25,864.730	9,845.086	17,944.776	30,369.955
Ind_Pay_Gap$_t$ (FF30-size median)	12,785	15,211.558	21,389.916	3,926.408	8,339.258	18,167.901
Ind_Pay_Gap$_t$ (SIC3) ($000)	9,404	16,148.932	22,456.673	3,996.673	9,380.435	19,065.953
Ind_Pay_Gap$_t$ (SIC3-size median)	8,674	9,965.364	18,555.532	1,037.812	4,188.025	11,101.430
Firm_Gap$_t$ ($000)	12,806	3,101.145	3,493.354	807.544	1,910.200	4,036.991
CEO_Delta$_t$ ($000)	12,806	791.810	8,674.627	77.749	202.615	528.848
CEO_Vega$_t$ ($000)	12,806	136.128	250.159	18.510	56.927	156.010
Scale_Ind_Pay_Gap$_t$ (FF30)	12,806	14.032	23.399	2.292	6.052	15.018
Scale_Ind_Pay_Gap$_t$ (SIC3)	9,404	9.907	24.756	1.181	3.417	9.299
Scale_Firm_Gap$_t$	12,806	0.608	0.173	0.521	0.639	0.724
Scale_CEO_Delta$_t$	12,806	0.179	0.426	0.031	0.062	0.128
Scale_CEO_Vega$_t$	12,806	0.028	0.029	0.009	0.020	0.038
Firm characteristics						
Total_Assets$_t$ ($000,000)	12,806	5,716.038	21,609.588	475.736	1,276.230	3,761.120
R&D$_t$	12,806	0.043	0.062	0.000	0.016	0.065
Cash$_t$	12,806	0.174	0.184	0.032	0.104	0.259
ROA$_t$	12,806	0.128	0.122	0.087	0.133	0.182
Capital_Invest$_t$	12,806	0.239	0.191	0.097	0.184	0.326
Leverage$_t$	12,806	0.196	0.162	0.034	0.188	0.307
Capital_Expend$_t$	12,806	0.047	0.042	0.020	0.035	0.060
Q$_t$	12,806	1.974	1.250	1.193	1.580	2.275
Prodmkt_Fluid$_t$	12,806	6.015	3.097	3.687	5.456	7.691
KZ_Index$_t$	12,806	-5.431	11.818	-5.942	-1.884	0.210
Firm_Age$_t$ (years)	12,806	29.076	19.462	14.000	23.000	41.000
CEO characteristics						
CEO_Founder$_t$ (dummy)	12,806	0.067				
CEO_Retire$_t$ (dummy)	12,798	0.071				
Industry level and instrumental variables						
Ind_CEO_Comp$_t$ ($000)	12,806	472,712.850	374,244.630	131,587.290	374,891.432	808,128.888
Geo_Pay_Rank$_t$	12,806	0.161	0.165	0.044	0.111	0.214
Ind_#CEOs$_t$	12,806	112.671	80.431	38.000	69.000	189.000

(continued)

Panel B: Correlation table

		1	2	3	4	5	6	7	8	9	10	11	12
1	*Prod_Innov*	1.00											
2	*Prod_Announce*	0.12^{***}	1.00										
3	*nPats*	0.09^{***}	0.28^{***}	1.00									
4	*nCits*	0.11^{***}	0.29^{***}	0.94^{***}	1.00								
5	*PatValue*	0.13^{***}	0.27^{***}	0.61^{***}	0.63^{***}	1.00							
6	*CEO_Delta*	0.01	0.11^{***}	0.07^{***}	0.07^{***}	0.04^{*}	1.00						
7	*CEO_Vega*	0.06^{***}	0.23^{***}	0.29^{***}	0.26^{***}	0.09^{***}	0.05^{***}	1.00					
8	*Total_Assets*	0.04^{**}	0.20^{***}	0.24^{***}	0.19^{***}	0.05^{**}	0.03^{*}	0.31^{***}	1.00				
9	*R&D*	0.09^{***}	0.20^{***}	0.21^{***}	0.31^{***}	0.34^{***}	0.01	-0.03^{*}	-0.11^{***}	1.00			
10	*Cash*	0.05^{**}	0.10^{***}	0.02	0.14^{***}	0.12^{***}	0.04^{**}	-0.07^{***}	-0.13^{***}	0.57^{***}	1.00		
11	*ROA*	-0.03^{*}	0.08^{***}	0.11^{***}	0.09^{***}	-0.01	0.06^{***}	0.14^{***}	0.04^{*}	-0.16^{***}	-0.15^{***}	1.00	
12	*Prodmkt_Fluid*	0.12^{***}	0.20^{***}	0.13^{***}	0.21^{***}	0.18^{***}	0.07^{***}	0.14^{***}	0.12^{***}	0.45^{***}	0.41^{***}	-0.12^{***}	1.00

Table 25 ITIs and product innovation

ITIs measure	*ITIs based on FF30 industry classification*				*ITIs based on SIC3 industry classification*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	2SLS			OLS	2SLS		
		1st stage	2nd stage			1st stage	2nd stage	
Dependent variable	*Prod_Innov*$_{t+1}$	*Ln(Ind_Pay_Gap)*$_t$	*Prod_Innov*$_{t+1}$	*Prod_Innov*$_{t+2}$	*Prod_Innov*$_{t+1}$	*Ln(Ind_Pay_Gap)*$_t$	*Prod_Innov*$_{t+1}$	*Prod_Innov*$_{t+2}$
Predicted ***Ln(Ind_Pay_Gap)***$_t$			**0.014*****	**0.012*****			**0.014*****	**0.014*****
			(4.47)	(3.12)			(3.82)	(3.06)
Ln(Ind_Pay_Gap)$_t$	0.003**				0.001			
	(2.02)				(0.88)			
Ln(Firm_Gap)$_t$	0.003**	-0.134***	0.004***	0.004**	0.002	-0.163***	0.004**	0.004**
	(2.49)	(-17.69)	(3.40)	(2.45)	(1.33)	(-15.16)	(2.53)	(2.25)
Ln(CEO_Delta)$_t$	-0.006***	-0.011**	-0.006***	-0.007***	-0.006***	-0.023***	-0.006***	-0.007***
	(-5.37)	(-1.99)	(-5.35)	(-5.09)	(-5.33)	(-3.04)	(-5.22)	(-4.34)
Ln(CEO_Vega)$_t$	0.001	0.009*	0.001	0.002**	0.002	-0.001	0.002*	0.002
	(1.38)	(1.91)	(1.53)	(2.01)	(1.54)	(-0.10)	(1.82)	(1.56)
Ln(Total_Assets)$_t$	0.007***	-0.067***	0.008***	0.009***	0.007***	-0.071***	0.008***	0.007***
	(5.04)	(-10.79)	(5.58)	(5.18)	(4.23)	(-7.56)	(4.91)	(3.58)
R&D$_t$	0.147***	-0.232**	0.151***	0.201***	0.117***	-0.179	0.120***	0.141***
	(4.90)	(-2.26)	(5.03)	(4.91)	(3.89)	(-1.28)	(3.99)	(3.53)
Cash$_t$	0.002	0.004	0.003	0.015	0.002	-0.094*	0.003	0.016
	(0.25)	(0.11)	(0.25)	(1.14)	(0.19)	(-1.77)	(0.32)	(1.19)
ROA$_t$	-0.050***	0.055	-0.049***	-0.040***	-0.036***	-0.005	-0.035***	-0.024*
	(-4.17)	(1.45)	(-4.18)	(-2.98)	(-3.01)	(-0.09)	(-3.02)	(-1.77)
Capital_Invest$_t$	-0.033***	0.047	-0.032***	-0.029*	-0.020	-0.008	-0.018	-0.015
	(-2.70)	(0.88)	(-2.67)	(-1.91)	(-1.24)	(-0.09)	(-1.16)	(-0.74)
Leverage$_t$	0.023***	0.180***	0.022**	0.005	0.023**	0.031	0.024**	0.009
	(2.61)	(5.08)	(2.49)	(0.44)	(2.29)	(0.55)	(2.43)	(0.71)
Capital_Expend$_t$	0.041	-0.368**	0.037	0.078	0.050	-0.312	0.047	0.083
	(1.05)	(-2.13)	(0.94)	(1.57)	(1.16)	(-1.30)	(1.12)	(1.48)
Q$_t$	0.001	-0.011**	0.001	-0.000	0.000	0.005	0.000	-0.000
	(0.66)	(-2.23)	(0.58)	(-0.23)	(0.28)	(0.78)	(0.10)	(-0.17)
Ln(Prodmkt_Fluid)$_t$	0.018***	-0.019	0.018***	0.017***	0.019***	0.021	0.019***	0.017***
	(4.90)	(-1.16)	(4.90)	(3.30)	(4.10)	(0.84)	(3.98)	(2.97)
KZ_Index$_t$	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.000
	(0.29)	(1.21)	(0.10)	(0.46)	(0.54)	(1.53)	(0.29)	(0.89)
Ln(Firm_Age)$_t$	0.007***	-0.006	0.007***	0.006**	0.006**	-0.005	0.006**	0.007**

	(3.16)	(-0.73)	(3.26)	(2.22)	(2.50)	(-0.39)	(2.56)	(2.33)
Ln(Ind_#CEOs)$_t$	-0.020**	-1.275***	-0.022**	-0.039***	-0.011	-0.741***	-0.021***	-0.027***
	(-2.16)	(-20.95)	(-2.35)	(-3.10)	(-1.63)	(-10.03)	(-2.85)	(-2.89)
Ln(Ind_CEO_Comp)$_t$ (IV)		1.760***				0.962***		
		(60.05)				(22.34)		
Geo_Pay_Rank$_t$ (IV)		-0.221***				-0.397***		
		(-4.26)				(-4.80)		
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,669	12,806	12,669	12,210	9,299	9,399	9,304	8,918
Adj. R-squared	0.119	0.775	0.119	0.151	0.147	0.745	0.153	0.192
Overidentification, relevance, and exogeneity tests								
Exogeneity tests: p-value of Hausman test			0.000***	0.002***			0.000***	0.001***
First-stage *F*-statistics			1784.97***	1717.91***			269.71***	278.12***
Hansen's *J*-statistics (Over-id test)			0.216	0.676			0.678	0.437

Table 26 ITIs and patent-based innovation

Panel A: ITIs based on FF30 industry classification					
	(1)	(2)	(3)	(4)	(5)
	1^{st} stage	2^{nd} stage			
Dependent variable	*Ln(Ind_Pay_Gap)$_t$*	*nPats$_{t+3}$*	*InnovEff$_{t+3}$*	*nCits$_{t+3}$*	*PatValue$_{t+3}$*
Predicted ***Ln(Ind_Pay_Gap)$_t$***		**-0.137*****	**-0.020*****	**-0.232*****	**-0.018*****
		(-4.45)	(-3.44)	(-4.78)	(-3.59)
Ln(Firm_Gap)$_t$	-0.135***	-0.012	-0.000	-0.017	-0.001
	(-17.12)	(-0.81)	(-0.00)	(-0.69)	(-0.62)
Ln(CEO_Delta)$_t$	-0.011*	-0.038***	0.001	-0.056**	0.000
	(-1.94)	(-2.66)	(0.44)	(-2.23)	(0.03)
Ln(CEO_Vega)$_t$	0.012**	0.039***	0.002	0.088***	0.003
	(2.36)	(3.31)	(0.92)	(4.42)	(1.64)
Ln(Total_Assets)$_t$	-0.071***	0.391***	-0.009***	0.582***	0.036***
	(-11.06)	(16.31)	(-3.02)	(16.28)	(12.64)
R&D$_t$	-0.200*	4.484***		7.861***	0.616***
	(-1.85)	(9.98)		(10.03)	(8.72)
Cash$_t$	-0.000	0.141	-0.014	0.702***	0.045**
	(-0.00)	(1.09)	(-0.86)	(3.01)	(2.05)
ROA$_t$	0.039	0.551***	0.033***	1.104***	0.047**
	(0.97)	(4.26)	(2.77)	(4.82)	(2.04)
Capital_Invest$_t$	0.054	-0.521***	0.038	-1.155***	-0.077***
	(0.97)	(-2.74)	(1.19)	(-3.77)	(-2.98)
Leverage$_t$	0.193***	-0.452***	-0.015	-0.711***	-0.016
	(5.19)	(-3.67)	(-0.93)	(-3.37)	(-0.82)
Capital_Expend$_t$	-0.452**	1.651***	0.103	3.393***	0.336***
	(-2.48)	(3.33)	(1.18)	(4.33)	(4.02)
Q$_t$	-0.012**	0.100***	0.002	0.142***	0.008***
	(-2.21)	(6.56)	(0.93)	(5.48)	(3.29)
Ln(Prodmkt_Fluid)$_t$	-0.021	-0.068	-0.019**	-0.040	-0.001
	(-1.26)	(-1.26)	(-2.29)	(-0.46)	(-0.07)
KZ_Index$_t$	0.001	0.002	-0.000	0.007***	0.001***
	(1.36)	(1.55)	(-0.40)	(2.85)	(3.19)
Ln(Firm_Age)$_t$	-0.007	0.095***	0.001	0.046	-0.006
	(-0.80)	(2.85)	(0.33)	(0.84)	(-1.27)
Ln(Ind_#CEOs)$_t$	-1.287***	0.161	0.046**	0.338**	0.013
	(-20.20)	(1.63)	(2.30)	(2.10)	(0.87)
Ln(Ind_CEO_Comp)$_t$ (IV)	1.756***				
	(56.16)				
Geo_Pay_Rank$_t$ (IV)	-0.203***				
	(-3.72)				
Year dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes
Observations	11,622	11,622	7,594	11,622	10,083
Adj. R-squared	0.774	0.484	0.154	0.452	0.325
Overidentification, relevance, and exogeneity tests					
Exogeneity tests: p-value of Hausman test		0.000***	0.000***	0.000***	0.000***
First-stage *F*-statistics		1592.67***	1003.02***	1592.67***	1367.32***
Hansen's *J*-test (Over-id test)		1.090	3.489*	2.075	9.979***

Panel B: ITIs based on SIC3 industry classification					
	(1)	(2)	(3)	(4)	(5)
	1st stage	2nd stage			
Dependent variable	*Ln(Ind_Pay_Gap)* $_t$	$nPats_{t+3}$	$InnovEff_{t+3}$	$nCits_{t+3}$	$PatValue_{t+3}$
Predicted ***Ln(Ind_Pay_Gap)*** $_t$		**-0.094*****	**-0.028*****	**-0.158*****	**-0.012****
		(-2.82)	(-3.82)	(-2.85)	(-2.31)
Ln(Firm_Gap) $_t$	-0.166***	-0.009	-0.002	-0.015	-0.002
	(-14.48)	(-0.59)	(-0.68)	(-0.56)	(-0.86)
Ln(CEO_Delta) $_t$	-0.028***	-0.026	-0.001	-0.036	0.002
	(-3.50)	(-1.60)	(-0.23)	(-1.24)	(0.68)
Ln(CEO_Vega) $_t$	0.002	0.038***	0.002	0.090***	0.004**
	(0.29)	(2.84)	(1.09)	(3.96)	(2.10)
Ln(Total_Assets) $_t$	-0.070***	0.416***	-0.011***	0.635***	0.038***
	(-6.99)	(15.89)	(-3.69)	(16.29)	(11.20)
$R\&D_t$	-0.104	3.628***		6.371***	0.581***
	(-0.70)	(8.64)		(8.65)	(7.90)
$Cash_t$	-0.078	0.094	-0.008	0.576**	0.041
	(-1.36)	(0.68)	(-0.53)	(2.25)	(1.59)
ROA_t	0.026	0.383***	0.027**	0.710***	0.037
	(0.46)	(2.96)	(2.41)	(3.07)	(1.53)
Capital_Invest $_t$	-0.009	0.205	0.052	-0.009	0.001
	(-0.10)	(0.78)	(1.54)	(-0.02)	(0.01)
$Leverage_t$	0.048	-0.443***	-0.016	-0.751***	0.008
	(0.77)	(-3.25)	(-1.00)	(-3.13)	(0.34)
Capital_Expend $_t$	-0.346	1.402***	0.080	2.603***	0.296***
	(-1.35)	(2.86)	(0.95)	(3.23)	(3.06)
Q_t	0.007	0.100***	0.004**	0.148***	0.010***
	(1.00)	(7.08)	(2.50)	(6.07)	(4.03)
Ln(Prodmkt_Fluid) $_t$	0.012	0.048	-0.013*	0.195**	0.013
	(0.42)	(0.83)	(-1.73)	(2.01)	(1.45)
KZ_Index $_t$	0.001*	-0.000	-0.000	0.002	0.000
	(1.66)	(-0.41)	(-0.70)	(0.95)	(1.02)
Ln(Firm_Age) $_t$	-0.006	0.110***	0.002	0.056	-0.006
	(-0.42)	(2.98)	(0.37)	(0.94)	(-1.06)
Ln(Ind_#CEOs) $_t$	-0.765***	0.083	0.020	0.220*	0.003
	(-9.82)	(1.20)	(1.41)	(1.87)	(0.28)
Ln(Ind_CEO_Comp) $_t$ *(IV)*	0.972***				
	(21.49)				
Geo_Pay_Rank $_t$ *(IV)*	-0.397***				
	(-4.53)				
Year dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes
Observations	8,447	8,453	5,954	8,453	7,402
Adj. R-squared	0.739	0.535	0.203	0.506	0.356
Overidentification, relevance, and exogeneity tests					
Exogeneity tests: p-value of Hausman test		0.001***	0.000**	0.000***	0.004***
First-stage *F*-statistics		253.69***	186.71***	253.69***	248.21***
Hansen's *J*-test (Over-id test)		1.472	3.237*	2.617	12.387***

Table 27 ITIs and routine product development

ITIs measure	*ITIs based on FF30 industry classification*		*ITIs based on SIC3 industry classification*	
	(1)	(2)	(3)	(4)
Dependent variable	*NonPat_ProdDev$_{t+1}$*	*NonPat_ProdDev$_{t+2}$*	*NonPat_ProdDev$_{t+1}$*	*NonPat_ProdDev$_{t+2}$*
Predicted ***Ln(Ind_Pay_Gap)$_t$***	**0.009*****	**0.010*****	**0.010****	**0.012*****
	(3.10)	(3.28)	(2.49)	(3.12)
Ln(Firm_Gap)$_t$	0.004***	0.003**	0.003**	0.003**
	(2.97)	(2.49)	(2.13)	(2.49)
Ln(CEO_Delta)$_t$	-0.005***	-0.005***	-0.005***	-0.004***
	(-4.39)	(-4.32)	(-4.30)	(-3.25)
Ln(CEO_Vega)$_t$	0.002*	0.001	0.002*	0.001
	(1.91)	(1.45)	(1.90)	(0.78)
Ln(Total_Assets)$_t$	0.004***	0.004***	0.003*	0.003*
	(2.98)	(3.17)	(1.71)	(1.68)
R&D$_t$	0.109***	0.089***	0.038*	0.035
	(3.68)	(2.91)	(1.70)	(1.58)
Cash$_t$	0.009	0.011	0.007	0.007
	(0.92)	(1.12)	(0.73)	(0.70)
ROA$_t$	-0.028**	-0.032***	-0.018	-0.021*
	(-2.56)	(-3.29)	(-1.33)	(-1.71)
Capital_Invest$_t$	-0.016	-0.020*	-0.010	-0.016
	(-1.33)	(-1.72)	(-0.68)	(-1.07)
Leverage$_t$	0.007	0.008	0.006	0.010
	(0.77)	(0.87)	(0.60)	(0.97)
Capital_Expend$_t$	0.042	0.054	0.036	0.040
	(1.06)	(1.45)	(0.89)	(1.01)
Q$_t$	-0.002*	0.000	-0.000	0.001
	(-1.90)	(0.29)	(-0.50)	(1.34)
Ln(Prodmkt_Fluid)$_t$	0.016***	0.012***	0.017***	0.014***
	(4.41)	(3.26)	(3.73)	(3.13)
KZ_Index $_t$	-0.000	0.000	-0.000	0.000
	(-0.79)	(0.91)	(-1.30)	(0.57)
Ln(Firm_Age)$_t$	0.004*	0.002	0.003	0.003
	(1.87)	(1.10)	(1.39)	(1.32)
Ln(Ind_#CEOs)$_t$	-0.028***	-0.039***	-0.016**	-0.024***
	(-3.03)	(-4.29)	(-2.12)	(-3.17)
Year dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Observations	12,806	12,142	9,404	8,868
Adj. R-squared	0.079	0.078	0.072	0.065

Overidentification, relevance, and exogeneity tests				
Exogeneity tests: p-value of Hausman test	0.001^{***}	0.008^{***}	0.014^{**}	0.000^{***}
First-stage F-statistics	1826.92^{***}	1696.26^{***}	276.71^{***}	278.25^{***}
Hansen's J-statistics	0.768	0.924	0.498	0.528
First-stage instruments' coefficients and significance				
$Ln(Ind\_CEO\_Comp)_t$	1.760^{***}	1.759^{***}	0.962^{***}	0.967^{***}
$Geo\_Pay\_Rank_t$	-0.221^{***}	-0.203^{***}	-0.397^{***}	-0.428^{***}

Table 28 Variability in the effect of ITIs on product innovation differing in product market competition

ITIs measure	*ITIs based on FF30 industry classification*		*ITIs based on SIC3 industry classification*	
	(1)	(2)	(3)	(4)
Dep var = *Prod_Innov*$_{t+2}$	*Prodmkt_Fluid* < median	*Prodmkt_Fluid* > median	*Prodmkt_Fluid* < median	*Prodmkt_Fluid* > median
Predicted ***Ln(Ind_Pay_Gap)***$_t$	**0.011***	**0.016*****	**0.012***	**0.017*****
	(1.70)	(2.91)	(1.95)	(2.71)
Controls$_t$	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Observations	6,158	6,052	4,494	4,424
Adj. R-squared	0.119	0.177	0.158	0.240
Overidentification, relevance, and exogeneity tests				
Exogeneity tests: p-value of Hausman test	0.148	0.005***	0.030**	0.009***
First-stage *F*-statistics	1129.361***	1189.01***	176.01***	80.94***
Hansen's *J*-statistics	0.003	1.895	0.010	1.396
First-stage instruments' coefficients and significance				
Ln(Ind_CEO_Comp)$_t$	1.672***	1.863***	0.929***	1.017***
Geo_Pay_Rank$_t$	-0.143**	-0.240***	-0.543***	-0.326***

Table 29 Myopic innovation strategy and CEO turnover

	(1)	(2)	(3)
Dependent variable		***Promote***	
NonPat_ProdDev$_t$	**2.956*****		
	(2.75)		
High_Myopic_Innov$_t$		**0.689****	0.253366
		(2.22)	(0.66)
High_Myopic_Innov$_t$* × *Ind_Pay_Gap$_t$			**0.0000182***
			(1.77)
Ind_Pay_Gap$_t$			-0.0000018
			(-0.15)
Ln(Total_Assets)$_t$	0.367***	0.377***	0.395***
	(3.50)	(3.71)	(3.79)
R&D$_t$	-0.987	-0.380	-0.416
	(-0.30)	(-0.13)	(-0.14)
Cash$_t$	1.291	1.327	1.312
	(0.99)	(1.11)	(1.09)
ROA$_t$	1.515	0.875	1.038
	(0.85)	(0.49)	(0.60)
Capital_Invest$_t$	0.238	0.212	0.219
	(0.18)	(0.13)	(0.13)
Leverage$_t$	-3.086**	-2.311*	-2.232*
	(-2.06)	(-1.67)	(-1.65)
Capital_Expend$_t$	1.227	1.526	1.284
	(0.22)	(0.28)	(0.24)
Q$_t$	-0.086	-0.150	-0.154
	(-0.58)	(-0.96)	(-0.98)
Ln(Prodmkt_Fluid)$_t$	-0.815	-0.623	-0.621
	(-1.63)	(-1.34)	(-1.34)
KZ_Index	0.014	0.007	0.006
	(0.71)	(0.43)	(0.40)
Ln(Firm_Age)$_t$	-0.212	-0.221	-0.218
	(-0.83)	(-0.96)	(-0.94)
Year dummies	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes
Observations	10,630	11,439	11,439
Pseudo R-squared	0.067	0.068	0.060

Table 30 Effect of ITIs on product innovation using enforceability of non-competition agreements

Dependent var = *Prod_Innov*$_{t+1}$	*ITIs based on FF30 industry classification*			*ITIs based on SIC3 industry classification*		
	(1)	(2)	(3)	(4)	(5)	(6)
	#In-state competitors > 25th pctl	#In-state competitors > 50th pctl	#In-state competitors > 75th pctl	#In-state competitors > 25th pctl	#In-state competitors > 50th pctl	#In-state competitors > 75th pctl
Ln(Ind_Pay_Gap)$_t$* × *Non_Compete$_t$	**-0.005**	**-0.008****	**-0.020*****	**-0.008***	**-0.016*****	**-0.028*****
	(-1.48)	(-2.31)	(-2.66)	(-1.93)	(-2.83)	(-2.62)
Ln(Ind_Pay_Gap)$_t$	0.003	0.003	0.001	0.001	0.003	0.003
	(1.31)	(1.06)	(0.21)	(0.34)	(1.05)	(0.80)
Non_Compete$_t$	0.056	0.089**	0.223***	0.090**	0.163***	0.295***
	(1.60)	(2.48)	(2.95)	(2.15)	(3.00)	(2.95)
Controls$_t$	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,372	6,418	3,199	4,739	3,333	1,616
Adj. R-squared	0.126	0.143	0.165	0.170	0.198	0.214

Table 31 ITIs and product announcements, 2nd stage 2SLS estimation

ITIs measure	*ITIs based on FF30 industry classification*		*ITIs based on SIC3 industry classification*	
	(1)	(2)	(3)	(4)
Dependent variable	*$Prod\_Announce_{t+1}$*	*$Prod\_Announce_{t+2}$*	*$Prod\_Announce_{t+1}$*	*$Prod\_Announce_{t+2}$*
Predicted ***$Ln(Ind\_Pay\_Gap)_t$***	**0.081*****	**0.063****	**0.095****	**0.076****
	(2.92)	(2.27)	(2.33)	(1.97)
$Ln(Firm\_Gap)_t$	0.007	0.015	0.024	0.030*
	(0.49)	(1.00)	(1.37)	(1.70)
$Ln(CEO\_Delta)_t$	-0.002	0.001	-0.007	-0.005
	(-0.17)	(0.10)	(-0.40)	(-0.31)
$Ln(CEO\_Vega)_t$	0.002	-0.004	0.002	-0.004
	(0.18)	(-0.42)	(0.13)	(-0.37)
$Ln(Total\_Assets)_t$	0.133***	0.126***	0.142***	0.133***
	(6.64)	(6.25)	(5.73)	(5.44)
$R\&D_t$	1.418***	1.391***	1.155***	1.111***
	(3.89)	(4.06)	(2.92)	(3.04)
$Cash_t$	0.130	0.134	0.182	0.222*
	(1.10)	(1.14)	(1.36)	(1.67)
ROA_t	0.046	-0.012	0.020	0.023
	(0.27)	(-0.07)	(0.11)	(0.13)
$Capital\_Invest_t$	-0.160	0.024	-0.196	-0.148
	(-1.38)	(0.20)	(-0.98)	(-0.73)
$Leverage_t$	-0.189*	-0.180*	-0.209*	-0.183*
	(-1.93)	(-1.92)	(-1.79)	(-1.66)
$Capital\_Expend_t$	0.984*	0.572	1.208*	1.060*
	(1.78)	(1.02)	(1.96)	(1.77)
Q_t	0.035**	0.040***	0.033*	0.039**
	(2.21)	(2.62)	(1.92)	(2.41)
$Ln(Prodmkt\_Fluid)_t$	0.079*	0.072*	0.094*	0.060
	(1.91)	(1.75)	(1.71)	(1.09)
KZ_Index	0.002	0.001	0.002	0.002
	(1.22)	(0.92)	(1.15)	(1.25)
$Ln(Firm\_Age)_t$	-0.010	-0.022	0.037	0.023
	(-0.36)	(-0.82)	(1.10)	(0.72)
$Ln(Ind\_\#CEOs)_t$	-0.460***	-0.461***	-0.158*	-0.071
	(-4.21)	(-4.42)	(-1.84)	(-0.81)
Year dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Observations	4,620	4,601	3333	3317
Adj. R-squared	0.223	0.211	0.264	0.248
Overidentification, relevance, and exogeneity tests				
Exogeneity tests: p-value of Hausman test	0.020**	0.048**	0.058*	0.134
First-stage *F*-statistics	406.84***	406.97***	75.30***	76.51***
Hansen's *J*-statistics	0.486	1.001	0.767	1.333
First-stage instruments' coefficients and significance				
$Ln(Ind\_CEO\_Comp)_t$	1.847***	1.847***	0.963***	0.964***
$Geo\_Pay\_Rank_t$	-0.251***	-0.252***	-0.442***	-0.445***

Table 32 ITIs and innovation strategies with firm fixed effects, 2nd stage 2SLS estimation

Panel A: ITIs and product innovation				
ITIs measure	*ITIs based on FF30 industry classification*		*ITIs based on SIC3 industry classification*	
	(1)	(2)	(3)	(4)
Dependent variable	$Prod\_Innov_{t+1}$	$Prod\_Innov_{t+2}$	$Prod\_Innov_{t+1}$	$Prod\_Innov_{t+2}$
Predicted ***Ln(Ind_Pay_Gap)$_t$***	**0.010*** **	**0.016*** **	**0.012*** **	**0.015*** **
	(3.79)	(4.55)	(3.57)	(3.65)
Controls$_t$	Yes	Yes	Yes	Yes
Year and Firm fixed effects	Yes	Yes	Yes	Yes
Observations	12,536	12,090	9,133	8,758
Adj. R-squared	0.030	0.045	0.026	0.042
Overidentification, relevance, and exogeneity tests				
Exogeneity tests: p-value of Hausman test	0.005***	0.008***	0.001***	0.004***
First-stage *F*-statistics	1703.73***	1701.50***	298.33***	304.67***
Hansen's *J*-test (Over-id test)	6.667***	0.827	4.072**	5.330**
First-stage instruments' coefficients and significance				
Ln(Ind_CEO_Comp)$_t$	1.594***	1.595***	0.946***	0.956***
Geo_Pay_Rank$_t$	-0.557***	-0.533***	-1.286***	-1.386***

Panel B: ITIs and patent-based innovation								
ITIs measure	*ITIs based on FF30 industry classification*				*ITIs based on SIC3 industry classification*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	$nPats_{t+3}$	$InnovEff_{t+3}$	$nCits_{t+3}$	$PatValue_{t+3}$	$nPats_{t+3}$	$InnovEff_{t+3}$	$nCits_{t+3}$	$PatValue_{t+3}$
Predicted ***Ln*(*Ind_Pay_Gap*)$_t$**	**-0.118*** **	**-0.018*** **	**-0.095*** **	**-0.007***	**-0.064*** **	**-0.020*** **	**-0.038**	**-0.005**
	(-5.88)	(-4.28)	(-3.23)	(-1.70)	(-2.96)	(-4.68)	(-1.17)	(-1.16)
Controls$_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,531	7,517	11,531	10,006	8,322	5,854	8,322	7,290
Adj. R-squared	0.050	0.102	0.019	0.071	0.070	0.107	0.025	0.076
Overidentification, relevance, and exogeneity tests								
Exogeneity tests: p-value of Hausman test	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.047**	0.026**
First-stage *F*-statistics	1591.09***	995.08***	1591.08***	1358.85***	279.74***	250.38***	279.74***	255.98***
Hansen's *J*-test	5.161**	2.366	4.054**	0.056	3.116*	0.148	3.922**	0.013
First-stage instruments' coefficients and significance								
Ln(Ind_CEO_Comp)$_t$	1.586***	1.568***	1.586***	1.584***	0.967***	1.022***	0.967***	1.000***
Geo_Pay_Rank$_t$	-0.508***	-0.548***	-0.508***	-0.471***	-1.349***	-1.414***	-1.349***	-1.355***

Table 33 Effect of ITIs on innovation strategies in size-median industry specifications (2nd stage 2SLS estimation)

Panel A: ITIs and product innovation				
ITIs measure	*ITIs based on FF30 size-median industry classification*		*ITIs based on SIC3 size-median industry classification*	
	(1)	(2)	(3)	(4)
Dependent variable	*$Prod\_Innov_{t+1}$*	*$Prod\_Innov_{t+2}$*	*$Prod\_Innov_{t+1}$*	*$Prod\_Innov_{t+2}$*
Predicted ***$Ln(Ind\_Pay\_Gap)_t$***	**0.016*****	**0.011****	**0.017*****	**0.017****
	(4.23)	(2.26)	(2.87)	(2.52)
$Controls_t$	Yes	Yes	Yes	Yes
Year and Industry FE	Yes	Yes	Yes	Yes
Observations	12,159	11,715	7,399	7,088
Adj. R-squared	0.108	0.146	0.132	0.174
Overidentification, relevance, and exogeneity tests				
Exogeneity tests: p-value of Hausman test	0.000***	0.015**	0.003***	0.007***
First-stage *F*-statistics	385.23***	382.11***	102.91***	105.73***
Hansen's *J*-test (Over-id test)	0.740	1.700	0.883	1.995
First-stage instruments' coefficients and significance				
$Ln(Ind\_CEO\_Comp)_t$	1.474***	1.481***	0.861***	0.874***
$Geo\_Pay\_Rank_t$	-0.426***	-0.422***	-0.525***	-0.605***

Panel B: ITIs and patent-based innovation								
ITIs measure	*ITIs based on FF30 size-median industry classification*				*ITIs based on SIC3 size-median industry classification*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	*$nPats_{t+3}$*	*$InnovEff_{t+3}$*	*$nCits_{t+3}$*	*$PatValue_{t+3}$*	*$nPats_{t+3}$*	*$InnovEff_{t+3}$*	*$nCits_{t+3}$*	*$PatValue_{t+3}$*
Predicted ***$Ln(Ind\_Pay\_Gap)_t$***	**-0.145*****	**-0.022*****	**-0.240*****	**-0.017*****	**-0.116****	**-0.022*****	**-0.167***	**-0.018***
	(-3.53)	(-2.87)	(-3.72)	(-2.69)	(-1.97)	(-2.81)	(-1.74)	(-1.90)
$Controls_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,150	7,325	11,150	9,657	6,715	4,982	6,715	5,925
Adj. R-squared	0.482	0.139	0.449	0.320	0.540	0.175	0.502	0.340
Overidentification, relevance, and exogeneity tests								
Exogeneity tests: p-value of Hausman test	0.001***	0.001***	0.000***	0.000***	0.073*	0.011**	0.103	0.002***
First-stage *F*-statistics	355.19***	221.43***	355.19***	305.30***	100.56***	71.89***	100.56***	86.75***
Hansen's *J*-test	1.527	4.230**	2.527	11.138***	0.834	3.850**	1.412	12.516***
First-stage instruments' coefficients and significance								
$Ln(Ind\_CEO\_Comp)_t$	1.461***	1.492***	1.461***	1.448***	0.871***	0.956***	0.871***	0.865***
$Geo\_Pay\_Rank_t$	-0.413***	-0.638***	-0.413***	-0.416***	-0.575***	-0.735***	-0.575***	-0.656***

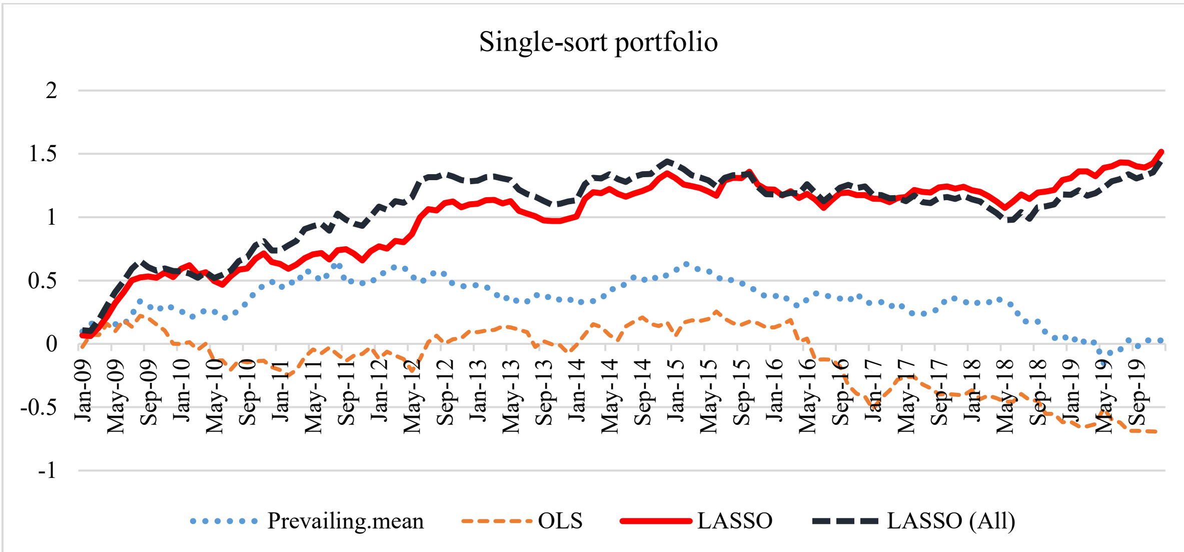
Table 34 Scaled measure of ITIs and innovation strategies (2nd stage 2SLS estimation)

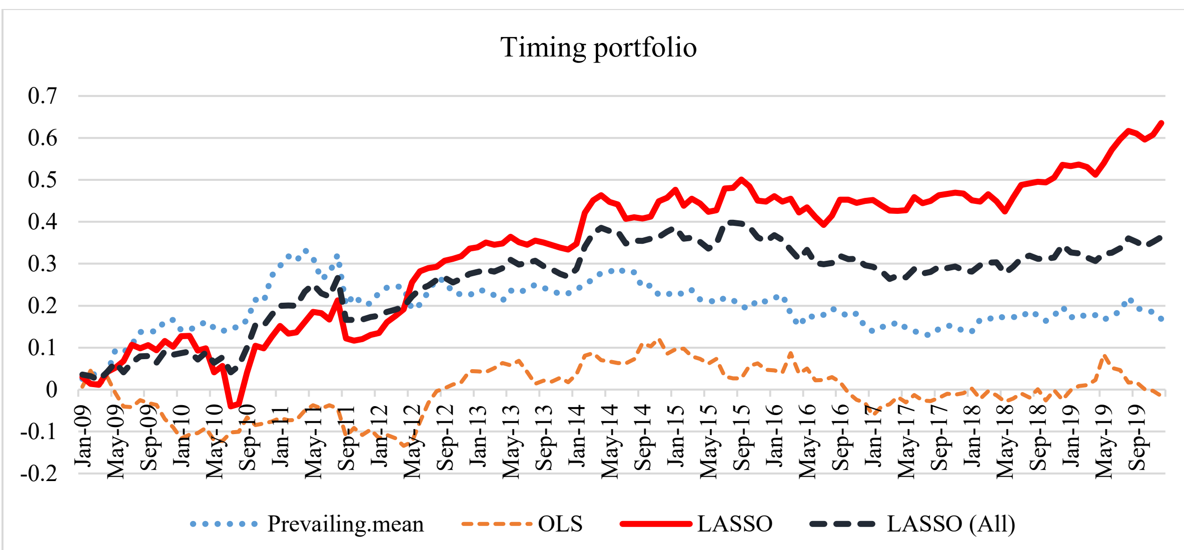
Panel A: Scaled measure of ITIs and product innovation				
ITIs measure	*Scaled measure of ITIs based on FF30 industry classification*		*Scaled measure of ITIs based on SIC3 industry classification*	
	(1)	(2)	(3)	(4)
Dependent variable	$Prod\_Innov_{t+1}$	$Prod\_Innov_{t+2}$	$Prod\_Innov_{t+1}$	$Prod\_Innov_{t+2}$
Predicted ***Scale_Ind_Pay_Gap***$_t$	**0.001*** **	**0.001*** **	**0.001*** **	**0.001*** **
	(3.94)	(2.38)	(3.82)	(3.11)
$Controls_t$	Yes	Yes	Yes	Yes
Year and Industry FE	Yes	Yes	Yes	Yes
Observations	12,648	12,189	9,304	8,918
Adj. R-squared	0.105	0.145	0.131	0.159
Overidentification, relevance, and exogeneity tests				
Exogeneity tests: p-value of Hausman test	0.000***	0.028**	0.000***	0.005***
First-stage *F*-statistics	207.02***	201.24***	61.62***	59.48***
Hansen's *J*-test (Over-id test)	1.188	1.265	0.008	0.000
First-stage instruments' coefficients and significance				
$Ln(Ind\_CEO\_Comp)_t$	31.512***	31.33***	9.870***	9.855***
$Geo\_Pay\_Rank_t$	-9.166***	-9.315***	-7.646***	-7.678***

Panel B: Scaled measure of ITIs and patent-based innovation								
ITIs measure	*Scaled measure of ITIs based on FF30 industry classification*				*Scaled measure of ITIs based on SIC3 industry classification*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	$nPats_{t+3}$	$InnovEff_{t+3}$	$nCits_{t+3}$	$PatValue_{t+3}$	$nPats_{t+3}$	$InnovEff_{t+3}$	$nCits_{t+3}$	$PatValue_{t+3}$
Predicted ***Scale_Ind_Pay_Gap***$_t$	**-0.007*** **	**-0.001*** **	**-0.011*** **	**-0.001*** **	**-0.007** **	**-0.001*** **	**-0.010* **	**-0.001* **
	(-3.74)	(-3.02)	(-3.84)	(-2.96)	(-2.19)	(-3.14)	(-1.86)	(-1.66)
$Controls_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,601	7,587	11,601	10,063	7,784	5,608	7,784	6,853
Adj. R-squared	0.481	0.146	0.451	0.329	0.522	0.123	0.496	0.345
Overidentification, relevance, and exogeneity tests								
Exogeneity tests: p-value of Hausman test	0.000***	0.004***	0.000***	0.034**	0.005***	0.001***	0.014**	0.015**
First-stage *F*-statistics	186.85***	122.54***	186.84***	154.56***	60.61***	50.61***	60.61***	52.75***
Hansen's *J*-test	1.359	3.655*	2.081	10.186***	1.249	2.731*	1.894	12.035***
First-stage instruments' coefficients and significance								
$Ln(Ind\_CEO\_Comp)_t$	30.825***	30.053***	30.825***	29.595***	13.468***	15.661***	13.468***	13.312***
$Geo\_Pay\_Rank_t$	-9.131***	-7.909***	-9.131***	-8.730***	-9.598***	-9.883***	-9.598***	-9.148***

FIGURES

Figure 1 Log cumulative returns for the single-sort portfolio and the timing portfolio





APPENDIX A: Frequency of the out-of-sample LASSO selection

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Regressand								
Regressor	Cocoa	Coffee	Copper	Corn	Cotton	Crude Oil	Feeder Cattle	Gasoline	Gold
Cocoa1	41	25			3	6			
Cocoa2	35	8			12		1	2	1
Coffee1	52	23	23		19		4	3	6
Coffee2	29	38	35	35	21	1	27	2	6
Copper1	22	5	34			1	22	6	
Copper2	39		20		23	31		40	
Corn1			11		1	2		4	
Corn2		5	5	1	3	19	7	46	1
Cotton1	13	13	15	10	21	15	47	22	3
Cotton2	1	10		9	18	15			
Crude Oil1	2	2		3	5	16		2	
Crude Oil2	1	34					20		
Feeder Cattle1			47	2	3	13		26	
Feeder Cattle2	22		8			1		6	
Gasoline1			1			15	5	6	4
Gasoline2	2	1		1	2		5	3	3
Gold1	27		15					6	6
Gold2	6			2	1	4	1	8	
Heating Oil1		8	1	7		2		1	
Heating Oil2					23	3	10		
Kansas Wheat1	8				3				
Kansas Wheat2	5	3			4	2		5	
Lean Hogs1	6	33	4	71	46	1	8	1	3
Lean Hogs2	5	7	13		2	1	6	5	2
Live Cattle1	5	34	8	46	1	16	12	30	7
Live Cattle2		8	2		61		10	1	1
Lumber1	12	28			32		3	1	
Lumber2	12		9	10	19	1	19	5	2
Milk1	8	57	1	72	7	1		4	6
Milk2	33	54	9	20	38	18	11	15	9
Natural Gas1	7	5	3	1	1	1	24	4	6
Natural Gas2	5	28	14		20	6	1	5	
Oats1	1	3	4		16		3		2
Oats2	20	2					14	1	
Orange Juice1	12	1	16		17	9	35	2	
Orange Juice2	27	25	4	16	1		17		
Palladium1	2	19	45	1	8	5	2	13	1
Palladium2	16	6		2	54	22	15	40	
Platinum1	15		66	5	26	13	14	18	
Platinum2	17		52	3		15		51	
Rough Rice1	30		1		2		19	2	
Rough Rice2	3	1		1	1	6	6	3	6
Silver1		4			2		11		
Silver2	3	4	4						
Soybean1	1				4	19		29	
Soybean2	2								
Soybean Meal1	9	9	3		1	13	2	14	
Soybean Meal2					1	1		14	
Soybean Oil1	7					3	1	1	
Soybean Oil2	1					6	1	9	
Sugar1	2			2	17		10	3	
Sugar2		5	40		60	15	2	26	
Wheat1		2	5			12	1	5	
Wheat2		32			3		2	2	
Grand Total	566	542	518	320	602	330	398	492	75

APPENDIX B: Summary statistics of commodity futures factors, extended time period

	Count	Mean (%)	Std (%)	Sharpe Ratio	Skew	Kurtosis	Min (%)	Max (%)
	Panel A: 1979-2019							
Trend	492	8.88*** (2.69)	21.10	0.42	0.08	0.18	-178.48	397.00
MOM	492	10.63*** (3.03)	22.44	0.47	-0.06	0.55	-290.81	224.30
BASIS	492	6.84** (2.22)	19.74	0.35	-0.32	2.71	-412.20	180.13
HP	492	8.03** (2.18)	18.80	0.43	0.33	0.43	-156.13	176.73
AVG	492	1.74 (0.95)	11.76	0.15	-0.36	2.77	-208.99	248.92
BASIS-MOM	492	12.09*** (3.75)	20.62	0.59	-0.40	2.08	-387.07	250.65
Value	492	3.71 (1.17)	20.25	0.18	-0.26	1.41	-260.38	212.14
	Panel B: 1983-2019							
Trend	444	9.77*** (2.81)	21.17	0.46	0.05	0.09	-170.05	248.92
MOM	444	8.95** (2.42)	22.55	0.40	-0.03	0.53	-290.81	250.65
BASIS	444	6.26* (1.93)	19.76	0.32	-0.31	2.99	-412.20	212.14
HP	312	8.03** (2.18)	18.80	0.43	0.33	0.43	-156.13	250.43
AVG	444	2.43 (1.3)	11.41	0.21	-0.32	3.28	-208.99	160.85
BASIS-MOM	444	10.66*** (3.13)	20.69	0.52	-0.41	2.26	-387.07	251.82
Value	444	3.58 (1.02)	21.24	0.17	-0.24	1.04	-260.38	203.99

APPENDIX C: Summary statistics of individual commodity futures

Ticker	Name	Sector	Count	Mean %	Std %	Skew	Kurtosis	Tstat
BO	Soybean Oil	agriculture	192	-0.56	25.14	-0.14	1.92	-0.09
C	Corn	agriculture	192	-3.9	28.93	0.25	0.77	-0.54
CC	Cocoa	agriculture	192	6.8	28.79	0.05	-0.05	0.94
CL	Crude Oil	energy	192	-1.16	31.02	-0.32	0.57	-0.15
CT	Cotton	agriculture	192	-2.28	28.14	0.08	0.71	-0.32
DA	Milk	agriculture	192	12.08***	17.32	0.52	2.24	2.79
FC	Feeder Cattle	livestock	192	4.07	15.70	0.18	0.30	1.04
GC	Gold	metal	192	8.2*	17.39	-0.10	0.70	1.88
HG	Copper	metal	191	11.5*	27.19	-0.11	4.09	1.69
HO	Heating Oil	energy	192	3.92	28.92	-0.24	0.63	0.54
JO	Orange Juice	agriculture	192	6.21	32.62	0.22	0.16	0.76
KC	Coffee	agriculture	192	-0.09	30.73	1.04	2.99	-0.01
KW	Kansas Wheat	agriculture	192	-4.43	30.92	0.52	1.33	-0.57
LB	Lumber	agriculture	192	-5.75	30.10	0.16	0.44	-0.76
LC	Live Cattle	livestock	192	4.7	14.49	0.11	0.39	1.30
LH	Lean Hogs	livestock	192	-1.88	28.99	0.48	1.73	-0.26
NG	Natural Gas	energy	192	-27.13**	42.06	0.19	1.54	-2.58
O	Oats	agriculture	192	2.76	33.28	0.28	0.60	0.33
PA	Palladium	metal	192	18.54**	32.04	0.03	3.14	2.32
PL	Platinum	metal	192	3.07	22.92	-0.66	3.37	0.54
RR	Rough Rice	agriculture	192	-4.89	24.39	0.00	0.67	-0.80
S	Soybean	agriculture	192	7.07	26.27	-0.31	0.72	1.08
SB	Sugar	agriculture	192	0.73	31.22	0.38	0.97	0.09
SI	Silver	metal	192	10.12	31.84	0.02	0.51	1.27
SM	Soybean Meal	agriculture	192	12.97*	30.93	0.22	1.04	1.68
W	Wheat	agriculture	192	-6.65	31.99	0.52	1.44	-0.83
XB	Gasoline	energy	170	4.2	31.98	-0.45	1.45	0.49

APPENDIX D: Chapter III variable definitions

Variable	Definition (sources)
	Firm characteristics
Total_Assets	Book value of Total_Assets in millions of constant dollars, CPI-adjusted. (Compustat)
R&D	R&D expenditures /Total_Assets, fillfed with 0 if missing. (Compustat)
Cash	$Cash$/Total Assets (Compustat)
ROA	Operating income before interest /Total Asset. (Compustat)
Capital_Invest	Investment in property, plant, and equipment /Total Asset (Compustat)
Leverage	(Long term debt + debt in current liabilities)/ (total asset) (Compustat)
Capital_Expend	Capital Expenditures /Total_Assets (Compustat)
Q	(market value of equity + book value of assets − book value of equity − balance sheet deferred taxes)/book value of assets, (Compustat)
Prodmkt_Fluid	The measure of firm-level competitive threats based on the description of a firm's product space and rivals move in their 10-Ks developed by Hoberg et al. (2014). A larger value of product market fluidity for the firm indicates a greater market threat from the competitors.
KZ_Index	Kaplan and Zingales (1997) 5-variable KZ_Index computed as -1.002^{*}Cash flow + 0.283^{*}Q + 3.139^{*}Leverage − 39.368^{*}Dividends − 1.315^{*}Cash holdings. (Compustat)
Firm_Age (years)	1 + the year under investigation − the first year the firm appears on the CRSP tapes. (CRSP)
	CEO characteristics
CEO_Founder	Value equals 1 if a CEO is the founder of the firm, otherwise 0 (ExecuComp)
CEO_Retire	Value equals 1 if the is older than 65 years old, otherwise 0. (ExecuComp)