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Introduction

Modeling and forecasting stock return and volatility have always been a subject of interest in academia and practice. This line of literature is important because stock returns and volatility are among the most important concepts in finance. Specifically, these elements are inputs for many asset pricing and risk management models, e.g., Black-Scholes and value-at-risk models, and many investment strategies within the mean-variance framework. Given the information on stock return and volatility patterns, the economic value of those trading strategies to investors is large, even after the transaction costs are controlled (Marquering and Verbeek (2004)).

The existing literature generally investigates stock return and volatility patterns at the market level. In practice, however, market participants do not always hold well-diversified market portfolios but often invest in certain sectors in which they have more private information or personal experience. Potential explanations for this approach are behavioral biases, financial constraints, and limited borrowing/lending opportunities. These facts strongly motivate our research projects. In

particular, this dissertation aims to model and forecast stock returns and volatility at the industry level.

Chapter 1 revisits the long-term return predictability pattern in the United States stock market and investigates whether this pattern holds across US industries. To answer this research question, we collect annual data on stock returns, dividend yields, and dividend growth in 34 industries from 1928 to 2018. Following the existing literature, we apply two methods: direct predictive regressions and the estimation implied by the first-order vector autoregression model (VAR). Furthermore, we conduct a Monte Carlo simulation, which is useful to account for the potential finite-sample bias identified by Stambaugh (1999) and to assess the robustness of our results.

Chapter 2 extends the work of Huang and Kilic (2019) by examining whether the ratio of gold to platinum prices (GP) leads US industry stock returns in-sample and out-of-sample over short and intermediate horizons. Motivated by the research of Campbell and Thompson (2008), we also test unconstrained and constrained out-of-sample return predictability by GP. Furthermore, we evaluate the economic significance of GP forecasts by comparing the out-of-sample performance of a GP-based with the passive buy-and-hold trading strategy.

Using several commodity indices as proxies for the commodity market, chapter 3 investigates the volatility transmission between commodities and major US equity sectors over the sample period from January 1991 to December 2019. The main motivation for this particular study is that, as we argue, commodity indices tend to better

capture the total risk exposure in the commodity market than crude oil. Thus, using indices to investigate the transmission and build the diversification strategies across two markets can eliminate potential bias. Moreover, we construct the hedge ratios and optimal weights for stock sectors in the pair with commodity indices. Finally, we demonstrate economic implications for investors by comparing the effectiveness of the diversification strategies using commodity indices and crude oil.

1

Stock Return Predictability: Evidence Across US Industries¹

1.1 Introduction

Stock returns are somewhat predictable. The existing literature confirms this statement, especially in the US stock market. The study of Cochrane (2008), developed from the present value identity of Campbell and Shiller (1988), demonstrates that given no rational bubbles,

¹This chapter is based on Pham, Quynh T, 2021a, Stock return predictability: Evidence across US industries, *Finance Research Letters* 38, 101531, presented at the 7th Paris Financial Management Conference, 2019 and the 18th ACATIS Value Seminar, 2020.

dividend yields must predict either long-run stock returns or long-run dividend growth to justify the fluctuations of current dividend yields. Cochrane (2008) then presents stronger evidence of predictability in long-run stock returns rather than long-run dividend growth. In fact, by applying the present value model in various settings, a vast body of literature documents a similar finding that the aggregate stock return in the United States, particularly in post-war years, is predictable. These studies include those of Campbell, Lo, and MacKinlay (1997); Cochrane (2005a); Chen (2009); Engsted and Pedersen (2010); Cochrane (2011); Kojien and Van Nieuwerburgh (2011); Rangvid, Schmeling, and Schrimpf (2014); Maio and Santa-Clara (2015); and Golez and Koudijs (2018).

From a different angle, this chapter investigates whether return predictability is valid across US industries. Addressing this research question is important because, in practice, investors do not always hold well-diversified market portfolios. Instead, investors often pursue an industry rotation strategy and/or concentrate their holdings in sectors in which they have more personal experience or private advantages (Døskeland and Hvide (2011) and Cici, Gehde-Trapp, Görnicke, and Kempf (2018)). According to Roche, Tompaidis, and Yang (2013), for example, household investors hold underdiversified portfolios that target a few industries, not only because of behavioral bias but also because of financial constraints and limited borrowing opportunities. Kacperczyk, Sialm, and Zheng (2005) find that mutual funds with a high industry concentration index earn an average annual return that

is 1.1% higher than funds with a low concentration index. Narayan, Ahmed, and Narayan (2017) further reveal that investors can benefit greatly from investing in certain sectors (See also Sorensen and Burke (1986); Grauer, Hakansson, and Shen (1990); and Ivković, Sialm, and Weisbenner (2008)). Given the information on return predictability across industries, this study assists investors in optimizing their portfolios, allocating capital, managing risks, and so on. Furthermore, by identifying any predictability heterogeneity over sectors, this chapter contributes to a better understanding of market and industry stocks. Gaining more knowledge on this matter might promote enhanced financial theories and models.

Our work relates to the limited research that examines return predictability based on dividend yields at the industry level. For instance, Beller, Kling, and Levinson (1998) and Ammann and Verhofen (2008) investigate the predictability of sector stock returns in the context of a Bayesian multivariate regression. However, both studies exclusively analyze a single period, such as quarterly or monthly predictability. Guidolin, McMillan, and Wohar (2013) also use dividend yields to forecast industry stock returns but focuses solely on monthly predictability over business cycles. Meanwhile, our study assesses the predictability pattern for different time horizons by applying multiple-horizon regressions. In addition, the papers mentioned above do not consider return predictability in relation to dividend growth predictability. As Cochrane (2008) discusses, isolating the predictability of these variables is not advisable because dividend yields should forecast either

stock returns or dividend growth. Our work attempts to fill these gaps.

To study return predictability across US industries, we collect annual data on stock returns, dividend yields, and dividend growth in 34 industries from 1928 to 2018. Following the existing literature, we apply two methods: direct predictive regressions and the estimation implied by the first-order vector autoregression model (VAR). Furthermore, we conduct a Monte Carlo simulation, which is useful to account for the potential finite-sample bias identified by Stambaugh (1999) and to assess the robustness of our results.

To summarize, our work makes two main contributions. First, this chapter confirms a general finding that value-weighted stock returns are predictable in the US setting. However, this predictability pattern does not always hold across US sectors. In fact, a predictability heterogeneity exists over industries. Stock returns tend to be predictable in sectors with large average firm or in large sectors such as, tobacco, communication, and petroleum and natural gas and less so in small sectors, such as coal, steel, and construction materials. Those findings concerning the relation between return predictability and market size are generally in line with those of the previous literature. In particular, Rangvid et al. (2014) find that stock returns are more predictable in countries in which the typical firm is large. Maio and Santa-Clara (2015) confirm that the return predictability pattern is valid for the portfolio of big stocks, but not for the portfolio of small stocks.

Second, our work provides a potential explanation for the cross-

industry predictability difference. In light of the dividend-smoothing phenomenon introduced by Chen, Da, and Priestley (2012), which is that dividend payouts are not determined solely by current earnings but also by past dividend payouts, our study presents supporting evidence for a higher level of dividend smoothness in large industries than in small industries. As demonstrated in the study by Chen et al. (2012), a high degree of dividend smoothness disconnects the link between dividend yield fluctuations and future dividends, which lessens dividend growth predictability and enhances return predictability. Consequently, stock returns are more predictable in large sectors, but less so in small sectors.

The findings in this chapter, although simple, have a significant implication for the asset pricing and portfolio optimization literature. Specifically, those findings suggest that dividend yields might be good proxies to predict returns in the value-weighted market and some large industries, but clearly not suitable for a few small industries.

The rest of the chapter proceeds as follows. Section 1.2 presents the methodology. Section 1.3 and 1.4 discuss data and empirical results, respectively. Additional results follow in section 1.5. Finally, section 1.6 concludes our findings.

1.2 Methodology

To test return predictability across industries, we apply two methods, namely, direct predictive regressions and the estimation implied by

the first-order VAR. In general, each method has its advantages. Estimates based on direct predictive regressions are more precise and less sensitive to assumptions imposed by the short-run VAR, whereas estimates based on the VAR model are easier to generalize and probably have better statistical properties. Accordingly, we use both methods in our analysis.

1.2.1 Direct predictive regressions

The literature on predictive regressions by dividend yields originates from the present value identity of Campbell and Shiller (1988):

$$dp_t \approx \sum_{j=1}^K \rho^{j-1} r_{t+j} - \sum_{j=1}^K \rho^{j-1} \Delta d_{t+j} + \rho^K dp_{t+K}, \quad (1.1)$$

where $dp_t = \ln(D_t) - \ln(P_t)$ is the log (the natural logarithm) dividend yield, r_t is the log stock return, $\Delta d_t = \ln(D_t) - \ln(D_{t-1})$ is the log dividend growth, K is the horizon length, and ρ is the linearization parameter. In line with conventional practice, we compute ρ from the mean log price-to-dividend \overline{pd} :

$$\rho = \frac{e^{\overline{pd}}}{1 + e^{\overline{pd}}}$$

Intuitively, (1.1) indicates that the stock price is high today only if future returns are low, future dividend growth is high, and/or in the long-run, investors expect prices to grow explosively faster than fundamentals, indicating rational bubbles. However, it is difficult to believe that prices explode in this way (Cochrane, 2005a, p 403). At

the macro level, Tirole (1985) finds that rational bubbles can only exist in a dynamically inefficient economy, which does not seem to be the US economy. Tirole (1982) demonstrates at the micro level that, given limited arbitrage opportunities, bubbles cannot occur in a model with a finite number of rational investors. Moreover, firms can rule out bubbles by imposing an upper limit on stock prices (Campbell et al., 1997, p 259). Hence, excluding rational bubbles in the long-horizon analysis is reasonable (Lewellen (2004) and Cochrane (2008)).

Following the literature, we use (1.2)-(1.4) to regress log future returns, log future dividend growth, and log future dividend yields on log current dividend yields. In addition, we calculate t -statistics associated with predictive coefficients by adopting the heteroskedasticity and autocorrelation-consistent (HAC) standard errors of Newey and West (1987).

$$\sum_{j=1}^K \rho^{j-1} r_{t+j} = a_r^K + b_r^K dp_t + \varepsilon_{t+K}^r \quad (1.2)$$

$$\sum_{j=1}^K \rho^{j-1} \Delta d_{t+j} = a_d^K + b_d^K dp_t + \varepsilon_{t+K}^d \quad (1.3)$$

$$\rho^K dp_{t+K} = a_{dp}^K + b_{dp}^K dp_t + \varepsilon_{t+K}^{dp} \quad (1.4)$$

Therefore, Equations (1.1)-(1.4) suggest that the subsequent relation between predictive coefficients holds for every horizon K :

$$1 \approx b_r^K - b_d^K + b_{dp}^K \quad (1.5)$$

The coefficients b_r^K , $-b_d^K$, and b_{dp}^K indicate the proportion of future

stock returns, future dividend growth, and/or price bubbles, respectively, in explaining the variance of current dividend yields. Furthermore, those coefficients signal the stock return or dividend growth that is predictable, assuming no rational price bubbles.

1.2.2 VAR-based estimation

Another standard method often utilized to validate return predictability is the VAR-based estimation. For simplification, we assume that log stock returns, log dividend growth, and log dividend yields follow the stationary restricted VAR(1).

$$r_{t+1} = a_r + b_r dp_t + \varepsilon_{t+1}^r \quad (1.6)$$

$$\Delta d_{t+1} = a_d + b_d dp_t + \varepsilon_{t+1}^d \quad (1.7)$$

$$dp_{t+1} = a_{dp} + \phi dp_t + \varepsilon_{t+1}^{dp} \quad (1.8)$$

where ϕ is the log dividend-yield autocorrelation.

In this section, the assumption of the first-order VAR is not an econometric restriction. According to Cochrane (2008), further lags of log dividend yields do not add much forecasting power to the VAR model. Given the VAR structure, (1.1) links the regression coefficients and the residuals ε_{t+1}^r , ε_{t+1}^d , and ε_{t+1}^{dp} through the subsequent equations:

$$b_r - b_d + \rho\phi = 1$$

$$\varepsilon_{t+1}^r = \varepsilon_{t+1}^d - \rho\varepsilon_{t+1}^{dp}$$

Moreover, for long-run regressions, we rewrite the direct predictive

regression as

$$\begin{aligned} \sum_{j=1}^K \rho^{j-1} r_{t+j} &= r_{t+1} + \rho r_{t+2} + \dots + \rho^{K-1} r_{t+K} \\ &= a_r^K + b_r dp_t + \rho b_r \phi dp_t + \dots + \rho^{K-1} b_r \phi^{K-1} dp_t + \varepsilon_{t+K}^r \end{aligned}$$

Mapping this function with formula (1.2), we obtain the following equation:

$$b_r^K = \sum_{j=1}^K \phi^{j-1} \rho^{j-1} b_r = \frac{b_r(1 - \rho^K \phi^K)}{1 - \rho\phi}$$

Similarly, we construct other coefficients implied by the VAR model as follows:

$$b_d^K = \frac{b_d(1 - \rho^K \phi^K)}{1 - \rho\phi}$$

$$b_{dp}^K = \rho^K \phi^K$$

The estimation based on the VAR model relative to direct regressions is more convenient because it provides a shortcut to compute predictive coefficients for every horizon K . We can even generalize long-run coefficients for the infinite horizon ($K \rightarrow \infty$ and $|\phi| \leq 1$) as

$$b_r^{LR} = \lim_{K \rightarrow \infty} \frac{b_r(1 - \rho^K \phi^K)}{1 - \rho\phi} = \frac{b_r}{1 - \rho\phi} \quad (1.9)$$

$$b_d^{LR} = \lim_{K \rightarrow \infty} \frac{b_d(1 - \rho^K \phi^K)}{1 - \rho\phi} = \frac{b_d}{1 - \rho\phi} \quad (1.10)$$

$$b_{dp}^{LR} = \lim_{K \rightarrow \infty} \rho^K \phi^K = 0 \quad (1.11)$$

Subject to these equations, Equation (1.5) becomes Equation (1.12):

$$b_r^{LR} - b_d^{LR} \approx 1 \quad (1.12)$$

Equation (1.12) implies that given no price bubbles, either b_r^{LR} or b_d^{LR} must be different from zero. In other words, either the long-run stock return or long-run dividend growth has to be predictable to justify the fluctuations in current dividend yields. Thus, forming a null hypothesis of return predictability without considering the corresponding hypothesis of dividend growth predictability and vice versa is not preferable. In this analysis, we test two joint hypotheses regarding long-run stock returns or dividend growth predictability across industries:

Hypothesis 1: Only long-run stock returns are predictable.

$$H_0 : b_r^{LR} = 1, b_d^{LR} = 0$$

Hypothesis 2: Only long-run dividend growth is predictable.

$$H_0 : b_r^{LR} = 0, b_d^{LR} = -1$$

1.3 Data

We obtain annual value-weighted returns with and without dividends in 49 US industries from 1927 to 2018 from [Kenneth R. French's website](#). After excluding industries with missing observations, our sample covers data on 34 industries.² In addition, we access monthly with-

²The industries are Aircraft (Aero), Agriculture (Agric), Automobiles and Trucks (Autos), Banking (Banking), Construction Materials (BldMt), Printing and Publishing (Books), Shipping Containers (Boxes), Business Services (BusSv), Chemicals (Chems), Electronic Equipment (Chips), Apparel (Clths), Coal (Coal), Pharmaceutical Products (Drugs), Electrical Equipment (ElcEq), Trading (Fin), Food Products (Food), Entertainment (Fun), Computers (Hardw), Con-

and without-dividend returns on the value-weighted portfolio of all stocks listed on the NYSE, AMEX, NASDAQ, and Arca between 1927 and 2018 from the Center for Research in Security Prices (CRSP). We then calculate the monthly dividend as the difference between monthly with- and without-dividend returns multiplied by the lagged price. To eliminate the seasonality effects of dividend payouts, we express the monthly data in annual terms as a standard practice, presuming that dividends are not reinvested. We do not assume dividend reinvestment because, as Chen (2009) argues, the reinvestment assumption makes dividend growth act like returns, which biases the dividend growth predictability test. Finally, we construct annual dividend yields and dividend growth for each industry and the aggregate data sets. Because we reserve 1927 data for lags, the sample period is from 1928 to 2018.

Table 1.1 presents the descriptive statistics of the annual data on log stock returns, log dividend yields, and log dividend growth for the value-weighted aggregate and 34 industry portfolios. On average, annual industry returns vary around the market return of 9% - between 6% and 11%. The highest mean returns belong to aircraft (Aero), pharmaceutical products (Drugs), computers (Hardw), and tobacco products (Smoke). These sectors also hold among the highest average

sumer Goods (Hshld), Insurance (Insur), Measuring and Control Equipment (LabEq), Machinery (Mach), Restaurants, Hotels, and Motels (Meals), Medical Equipment (MedEq), Non-Metallic and Industrial Metal Mining (Mines), Petroleum and Natural Gas (Oil), Retail (Rtail), Shipbuilding and Railroad Equipment (Ships), Tobacco Products (Smoke), Steel Works etc. (Steel), Communication (Telcm), Transportation (Trans), Textiles (Txtls), and Utilities (Util).

Table 1.1: Descriptive Statistics of the annual data

The table presents the descriptive statistics of the annual data on log stock returns r , log dividend growth Δd , and log dividend yields dp for the value-weighted aggregate and 34 industry portfolios. The sample period is from 1928 to 2018.

Industry	Log returns		Log dividend growth		Log dividend yields		
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	AR(1)
Market	0.09	0.20	0.04	0.14	-3.37	0.43	0.95
Aero	0.11	0.33	0.07	0.35	-3.52	0.63	0.88
Agric	0.08	0.25	0.04	0.31	-3.65	0.68	0.88
Autos	0.08	0.32	0.03	0.32	-3.14	0.50	0.85
Banks	0.11	0.26	0.05	0.22	-3.21	0.53	0.90
BldMt	0.09	0.25	0.04	0.32	-3.50	0.55	0.83
Books	0.07	0.33	0.05	0.33	-3.62	0.51	0.79
Boxes	0.10	0.20	0.06	0.17	-3.58	0.51	0.93
BusSv	0.08	0.28	0.04	0.26	-3.80	0.75	0.94
Chems	0.10	0.22	0.05	0.19	-3.40	0.32	0.82
Chips	0.09	0.34	0.05	0.35	-3.86	0.88	0.94
Clths	0.09	0.25	0.04	0.37	-3.56	0.76	0.88
Coal	0.06	0.39	0.03	0.65	-3.71	0.81	0.76
Drugs	0.11	0.19	0.06	0.14	-3.53	0.48	0.93
ElcEq	0.10	0.25	0.07	0.23	-3.57	0.40	0.81
Fin	0.09	0.29	0.05	0.26	-3.48	0.56	0.88
Food	0.10	0.17	0.05	0.14	-3.33	0.40	0.91
Fun	0.10	0.36	0.05	0.57	-4.00	1.11	0.89
Hardw	0.11	0.28	0.07	0.28	-4.11	1.00	0.96
Hshld	0.09	0.20	0.04	0.17	-3.46	0.46	0.92
Insur	0.09	0.22	0.05	0.16	-3.53	0.54	0.94
LabEq	0.10	0.23	0.06	0.28	-4.17	0.87	0.95
Mach	0.09	0.26	0.04	0.29	-3.50	0.60	0.88
Meals	0.10	0.28	0.06	0.34	-3.75	0.87	0.92
MedEq	0.11	0.23	0.05	0.19	-3.97	0.98	0.97
Mines	0.08	0.28	0.02	0.45	-3.29	0.57	0.72
Oil	0.10	0.21	0.05	0.18	-3.29	0.37	0.89
Rtail	0.10	0.23	0.06	0.22	-3.65	0.71	0.95
Ships	0.08	0.28	0.02	0.40	-3.42	0.74	0.85
Smoke	0.11	0.21	0.06	0.18	-3.00	0.25	0.74
Steel	0.06	0.30	0.01	0.38	-3.42	0.63	0.84
Telcm	0.09	0.18	0.03	0.17	-3.16	0.49	0.93
Trans	0.08	0.24	0.03	0.21	-3.52	0.63	0.95
Txtls	0.08	0.31	0.01	0.43	-3.73	1.10	0.95
Util	0.08	0.20	0.03	0.15	-2.95	0.35	0.89

dividend growth.

In contrast, over the sample period, coal and steel industries generate the lowest average return of 6%. Interestingly, the corresponding

standard deviations of the log returns in these industries are comparatively high, at more than 30%. This finding probably implies that investing in coal and/or steel stocks is less profitable and riskier than investing in other stocks or in the market index. Thus, investing in coal and steel sectors over the last 91 years does not sound optimal.

Additionally, Table 1.1 shows that a portfolio of utility stocks earns the highest average dividend yield, whereas the measuring and control equipment industry obtains the lowest yield. These numbers might reflect the differences between the two industry structures. Specifically, the utility sector sells non-durable and the measuring and control equipment sector sells durable products.

The last column of Table 1.1 presents the log dividend-yield autocorrelation. In general, extreme values of those coefficients in all sectors are less than unity, satisfying the necessary condition for long-horizon regressions. However, the degree of autocorrelation in log dividend yields is relatively high, ranging between 0.72 and 0.97. As Stambaugh (1999) addresses, a high degree of the log dividend-yield autocorrelation increases the finite-sample bias in predictive regressions. Nelson and Kim (1993) and Engsted and Pedersen (2014) recommend using a simulated-based analysis to minimize the possible bias. With this in mind, we conduct a Monte Carlo simulation to assess the robustness of our findings.

1.4 Empirical Results

1.4.1 Direct predictive regressions

Table 1.2 presents the coefficient results from 1-, 5-, 10-, and 20-year predictive regressions of log stock returns and log dividend growth on log dividend yields for the stock market and 34 stock industries. In general, three different cross-industry predictive patterns exist.

The upper panel of Table 1.2 presents the regression results of the stock market and 12 industries with predictable stock returns. For the stock market, the share of return predictability increases dramatically from 8% at the 1-year horizon to 55% and 80% at the 10- and 20-year horizons, respectively. Meanwhile, current dividend yields predict almost none of the future dividend growth across forecasting horizons. These findings confirm the prior literature that long-horizon stock returns in the US market are predictable whereas dividend growth is not.³ Similarly, the pattern of return predictability holds in 12 other industries, including chemicals, communication, utility, and so on. The predictive coefficients \hat{b}_r of those industries grow rapidly with the forecasting horizon and approach and go beyond unity. Note that those predictive coefficients do not have to be bounded between zero and one. For example, a coefficient in the utility sector that is higher than one implies that a high dividend yield forecasts an extremely high utility stock return. Moreover, the upper part of Table

³A very few studies are concerned about the non-stationarity issue of dividend yields. Using different unit root tests, we find dividend yields in the market, measuring and control equipment, and business services industries appear to have structural breaks. However, the findings of our analysis are also robust in subsamples.

Table 1.2: Direct predictive regressions

The table presents the coefficient results from 1-, 5-, 10-, and 20-year regressions of log stock returns and log dividend growth on log dividend yields for the stock market and 34 industries. Standard errors are Newey and West (1987) HAC standard errors. The coefficients in bold indicate that we could not reject the corresponding null hypotheses at the 5% significance level or better. The sample period is from 1928 to 2018.

Industry	Return Coefficients				Dividend Growth Coefficients			
	1 yr	5 yrs	10 yrs	20 yrs	1 yr	5 yrs	10 yrs	20 yrs
Market	0.08	0.32	0.55	0.80	-0.00	-0.03	-0.05	-0.10
Autos	0.07	0.30	0.75	1.05	-0.12	-0.27	0.19	0.20
Banks	0.11	0.35	0.72	0.89	-0.03	-0.13	0.11	-0.06
Books	0.14	0.65	0.68	0.64	-0.09	-0.13	-0.13	-0.38
Boxes	0.08	0.33	0.54	0.74	-0.02	-0.04	-0.08	-0.11
Chems	0.21	0.57	0.80	0.93	0.00	0.02	0.05	-0.09
ElcEq	0.15	0.47	0.53	0.66	-0.07	-0.10	-0.18	-0.38
Fin	0.15	0.38	0.71	0.95	0.00	-0.03	0.00	-0.21
Hardw	0.02	0.14	0.28	0.78	-0.04	-0.24	-0.41	-0.61
Oil	0.13	0.42	0.58	1.03	-0.01	0.01	-0.06	-0.17
Telcm	0.12	0.43	0.65	1.00	0.02	-0.03	-0.10	-0.08
Txtls	0.04	0.08	0.25	0.68	-0.04	-0.10	0.04	0.47
Util	0.18	0.63	0.93	1.15	0.03	0.03	0.03	-0.07
Aero	0.09	0.22	0.33	0.18	-0.06	-0.37	-0.62	-0.92
Agric	0.07	0.07	0.06	-0.05	-0.07	-0.48	-0.61	-0.90
Coal	0.01	0.20	0.18	0.39	-0.24	-0.27	-0.51	-0.50
Food	0.05	0.19	0.34	0.26	-0.07	-0.27	-0.32	-0.62
Fun	-0.01	0.00	0.04	0.00	-0.13	-0.41	-0.65	-0.87
Mines	0.01	-0.07	-0.13	0.05	-0.29	-0.79	-0.89	-0.82
Smoke	0.28	0.40	0.15	-0.32	-0.01	-0.43	-0.80	-1.25
Steel	0.03	0.18	0.33	0.22	-0.15	-0.37	-0.40	-0.68
BldMt	0.04	0.30	0.41	0.45	-0.15	-0.13	-0.12	-0.30
BusSv	0.06	0.25	0.26	0.27	-0.02	-0.13	-0.37	-0.51
Chips	0.03	0.23	0.38	0.54	-0.05	-0.16	-0.31	-0.41
Clths	0.03	0.07	0.05	0.00	-0.11	-0.24	-0.43	-0.69
Drugs	0.05	0.24	0.38	0.37	-0.05	-0.23	-0.34	-0.57
Hshld	0.05	0.29	0.56	0.78	-0.06	-0.18	-0.25	-0.33
Insur	0.04	0.19	0.38	0.51	-0.05	-0.13	-0.16	-0.30
LabEq	0.04	0.12	0.14	0.42	-0.03	-0.22	-0.44	-0.15
Mach	0.04	0.14	0.16	0.35	-0.11	-0.19	-0.35	-0.35
Meals	0.03	0.10	0.12	0.15	-0.08	-0.26	-0.52	-0.71
MedEq	0.00	0.00	0.11	0.23	-0.06	-0.32	-0.50	-0.68
Rtail	0.04	0.16	0.26	0.31	-0.03	-0.14	-0.28	-0.45
Ships	0.01	0.02	0.00	0.16	-0.16	-0.37	-0.38	-0.43
Trans	0.03	0.07	0.06	0.09	-0.05	-0.24	-0.38	-0.51

1.2 demonstrates that most of the return coefficients at 10- and 20-year horizons are indifferent from one and statistically significant at the 5% level. Hence, we cannot reject the null hypothesis that long-run stock returns are predictable in those sectors.

Notwithstanding, the middle panel of Table 1.2 presents the coefficient statistics of eight industries with predictable dividend growth. These sectors include aircraft, agriculture, food, and tobacco products, among others. In these industries, the ratios of dividend growth predictability are predominant and exceed up to 120% for the 20-year horizon. The negative sign of the predictive coefficients associated with dividend growth suggests that high current dividend yields signal low future dividend growth. Additionally, the majority of the long-horizon predictive coefficients \widehat{b}_d in this panel are statistically indifferent from minus one. In comparison, the return predictability slopes are modest and occasionally have wrong signs. This finding suggests that long-run dividend growth in those industries is predictable, whereas stock returns are not.

The lower panel presents the remaining industries in which either stock return or dividend growth predictability is unclear. The reason for the mentioned ambiguities is that dividend yields in some sectors, such as apparel, measuring and control equipment, and transportation, are highly autocorrelated. Thus, the correlation between current and future dividend yields do not vanish after 20 years. As a result, rational price bubbles account for some parts of the present-value predictability in these particular cases. In addition, that return or div-

idend growth predictability dominates each other within the 20-year horizon is not necessary but perhaps beyond the 20-year horizon. In the next section, we further test null hypotheses at the infinite horizon using the VAR model.

1.4.2 VAR-based long-run estimation

Table 1.3 presents long-run regression coefficients calculated using formulas (1.9) and (1.10) for the stock market and 34 stock industries. Similar to Table 1.2, Table 1.3 presents a predictability heterogeneity over US sectors.

The upper panel in Table 1.3 shows that return predictability is a common pattern in the market and nine industry portfolios. In the stock market, the long-run predictive coefficient \widehat{b}_r^{LR} is large and close to one, indicating that almost all of the dividend yield movements are explained by variations in long-run future stock returns. In contrast, the long-run predictive coefficient \widehat{b}_d^{LR} is -0.01 and statistically equal to zero. Accordingly, none of the long-run future dividend fluctuations relates to changes in current dividend yields. This finding again confirms that stock returns and not dividend growth are predictable in the US stock market. Moreover, the results for nine other sectors, including banking, trading, communication, and utility, are similar.

However, the pattern of return predictability does not hold in a few industries, such as coal, machinery, and entertainment. As indicated by the predictive coefficients, the majority of the variation in the current dividend yield results from varying expectations of future

Table 1.3: VAR-based long-run coefficients

The table presents long-run regression coefficients calculated using formulas (1.9) and (1.10) for the stock market and 34 industries, where ρ is corrected to satisfy the identity $\rho\hat{\phi} = 1 - \hat{b}_r + \hat{b}_d$. Standard errors (SE) are computed using the delta method and based on Newey and West (1987) HAC 1-year standard errors (See Appendix A.1 for more details). The t -statistics are computed under the respective null hypotheses. The sample period is from 1928 to 2018.

Industry	\hat{b}_r^{LR}	SE	$t(b_r^{LR} = 1)$	\hat{b}_d^{LR}	SE	$t(b_d^{LR} = -1)$
Market	0.99	0.41	-0.03	-0.01	0.41	2.42
Banks	0.80	0.27	-0.72	-0.20	0.27	2.96
Boxes	0.84	0.32	-0.48	-0.16	0.32	2.60
Chems	1.00	0.27	0.02	0.00	0.27	3.74
ElcEq	0.68	0.27	-1.19	-0.32	0.27	2.56
Fin	0.98	0.31	-0.07	-0.02	0.31	3.11
Oil	0.96	0.29	-0.14	-0.04	0.29	3.31
Smoke	0.95	0.27	-0.17	-0.05	0.27	3.47
Telcm	1.17	0.51	0.32	0.17	0.51	2.27
Util	1.18	0.22	0.83	0.18	0.22	5.36
Autos	0.37	0.32	-1.97	-0.63	0.32	1.15
BldMt	0.23	0.25	-3.03	-0.77	0.25	0.90
Clths	0.21	0.20	-3.93	-0.79	0.20	1.05
Coal	0.05	0.23	-4.19	-0.95	0.23	0.24
Fun	-0.06	0.27	-3.95	-1.06	0.27	-0.24
Mach	0.27	0.20	-3.67	-0.73	0.20	1.34
Meals	0.23	0.34	-2.23	-0.77	0.34	0.68
Mines	0.04	0.14	-6.66	-0.96	0.14	0.30
Ships	0.08	0.24	-3.89	-0.92	0.24	0.33
Steel	0.16	0.36	-2.37	-0.84	0.36	0.44
Aero	0.60	0.47	-0.86	-0.40	0.47	1.29
Agric	0.48	0.20	-2.58	-0.52	0.20	2.35
BusSv	0.73	0.42	-0.64	-0.27	0.42	1.75
Chips	0.34	0.65	-1.02	-0.66	0.65	0.52
Drugs	0.53	0.36	-1.32	-0.47	0.36	1.48
Food	0.45	0.29	-1.90	-0.55	0.29	1.54
Hardw	0.33	0.53	-1.26	-0.67	0.53	0.61
Hshld	0.46	0.37	-1.46	-0.54	0.37	1.23
Insur	0.43	0.46	-1.23	-0.57	0.46	0.94
LabEq	0.55	0.58	-0.76	-0.45	0.58	0.95
MedEq	-0.08	0.65	-1.67	-1.08	0.65	-0.13
Rtail	0.57	0.34	-1.25	-0.43	0.34	1.66
Trans	0.38	0.46	-1.36	-0.62	0.46	0.83
Txtls	0.49	0.55	-0.92	-0.51	0.55	0.88

long-run dividend growth in those sectors. The t -statistics further suggest rejecting the null of return, not dividend growth predictability at

the 5% significance level.

Although most of the results in Table 1.3 confirm the results in Table 1.2, conflicting findings exist for the automobiles and tobacco industries. These opposing results occur because, on the one hand, the direct predictive method does not concurrently test the statistical significance of the return or dividend growth predictive coefficients. Hence, the results in Table 1.2 might not reflect all of the implications of the present value identity. On the other hand, the restrictive assumption that VAR(1) fully captures the dynamics between variables seems to be invalid in some industries. Accordingly, the transition from short- to long-run regressions based on the VAR might be misleading in those cases. Engsted and Pedersen (2010) address the issue and recommend being cautious when using VAR-based long-run regressions.

Finally, the lower panel of Table 1.3 presents the remaining industries with an unclear predictability pattern. This result probably implies that VAR-based long-run estimation results inadequately support or reject the hypothesis of return or dividend growth predictability in those industries given the 5% significance level. Therefore, further analysis is necessary.

1.4.3 Simulation-based inference

As an alternative to asymptotic p -values based on the first-order VAR, following Cochrane (2008), we conduct Monte Carlo simulations and compute the joint probabilities that simulated coefficients are lower

(higher) than their sample values under the null of no return (dividend growth) predictability. According to Nelson and Kim (1993) and Engsted and Pedersen (2014), the simulation method is more powerful than the OLS regression because it reduces the finite-sample bias arising from the high degree of the log dividend-yield autocorrelation.

The procedure of Monte Carlo simulations is as follows:

1. Choose ρ and ϕ as their sample estimates.
2. Generate the first value dp_0 from the unconditional density

$$dp_0 \sim N[0, \sigma^2(\varepsilon^{dp})/(1 - \phi^2)]$$

3. Simulate VAR residuals by assuming that these residuals are normally distributed with means of zeros and variances equal to the sample variances.
4. Develop the VAR system further, based on the specific null. Under the null of no return predictability, for example, the VAR system takes the form

$$\begin{bmatrix} dp_{t+1} \\ \Delta d_{t+1} \\ r_{t+1} \end{bmatrix} = \begin{bmatrix} \phi \\ \rho\phi - 1 \\ 0 \end{bmatrix} dp_t + \begin{bmatrix} \varepsilon_{t+1}^{dp} \\ \varepsilon_{t+1}^d \\ \varepsilon_{t+1}^d - \rho\varepsilon_{t+1}^{dp} \end{bmatrix}$$

Adversely, under the null of no dividend growth predictability,

the system becomes

$$\begin{bmatrix} dp_{t+1} \\ \Delta d_{t+1} \\ r_{t+1} \end{bmatrix} = \begin{bmatrix} \phi \\ 0 \\ 1 - \rho\phi \end{bmatrix} dp_t + \begin{bmatrix} \varepsilon_{t+1}^{dp} \\ \varepsilon_{t+1}^r + \rho\varepsilon_{t+1}^{dp} \\ \varepsilon_{t+1}^r \end{bmatrix}$$

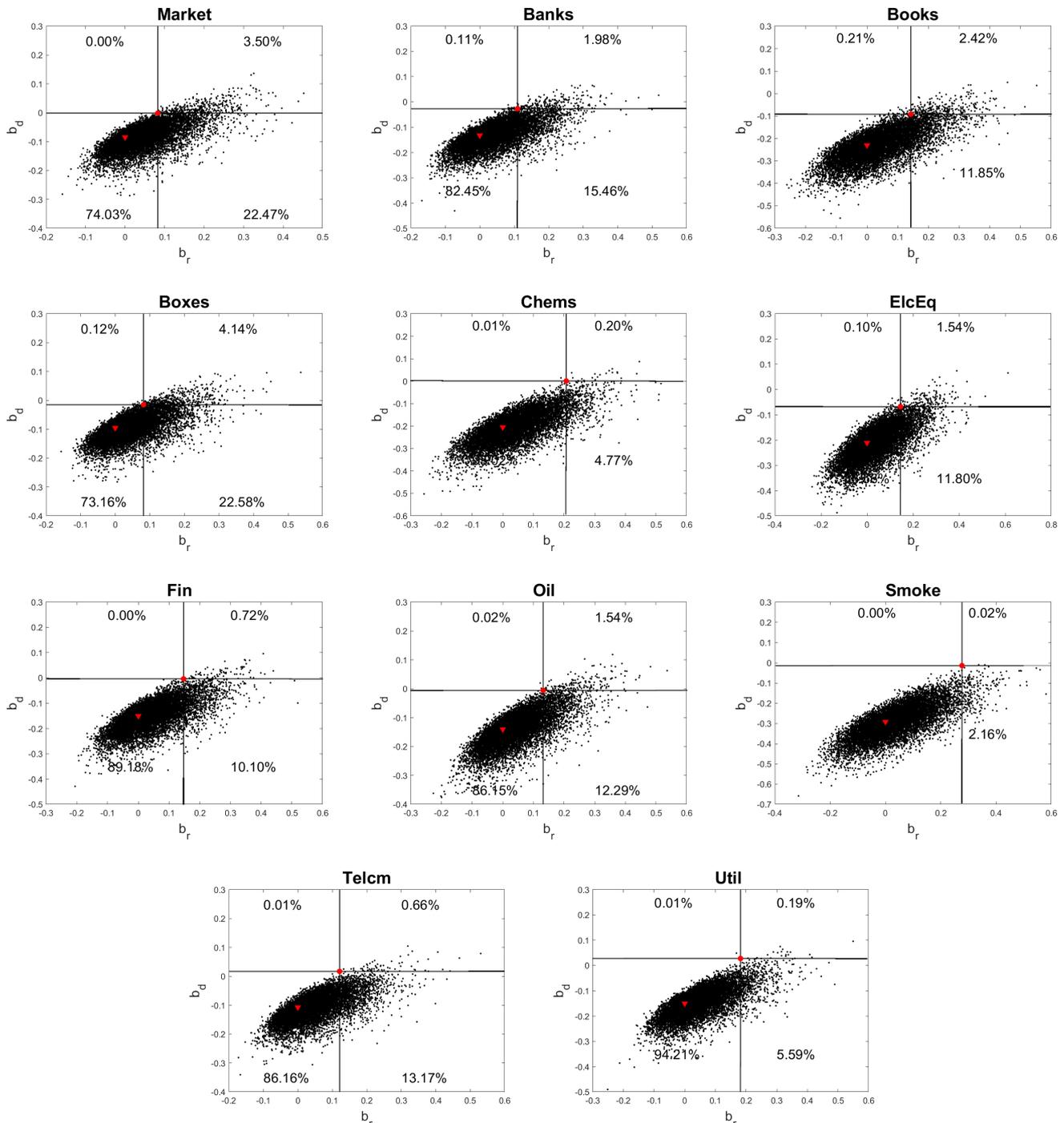
5. Run regressions (1.6)-(1.7) and collect simulated coefficients \widehat{b}_r and \widehat{b}_d .
6. Repeat the above steps 10,000 times.
7. Calculate the joint probabilities that the simulated coefficients are lower (higher) than their sample values. Those probabilities represent p -values for or against the null of no return predictability ($b_r = 0$) or no dividend growth predictability ($b_d = 0$).

Figures 1.1 and 1.2 present the joint distribution of the simulated predictive coefficients across industries, under the null of no return and no dividend growth predictability, correspondingly. To save space, we only include industries for which the evidence for or against the null is statistically significant at the 5% level or better.

At first glance, Figure 1.1 seems to provide evidence that advocates the null of unpredictable returns in the stock market. Approximate 26% of the simulated return coefficients b_r (all dots on the right of the vertical line in the plot) are larger than the sample estimate. Similarly, in eight other industries, except for chemicals and tobacco, the Monte Carlo simulation quite often (6% to 26% of the time) generates a larger-than-sample return coefficient. Therefore, by testing return predictability itself, we could not consistently reject the null hypoth-

Figure 1.1: Joint distribution under the null of no return predictability

The figure plots joint distribution of simulated predictive coefficients under the null of no return predictability. Small dots show simulation while large dots show sample estimates. The triangle gives the null. The percentage in each quadrant is the fraction of 10,000 simulations that falls within the quadrant.

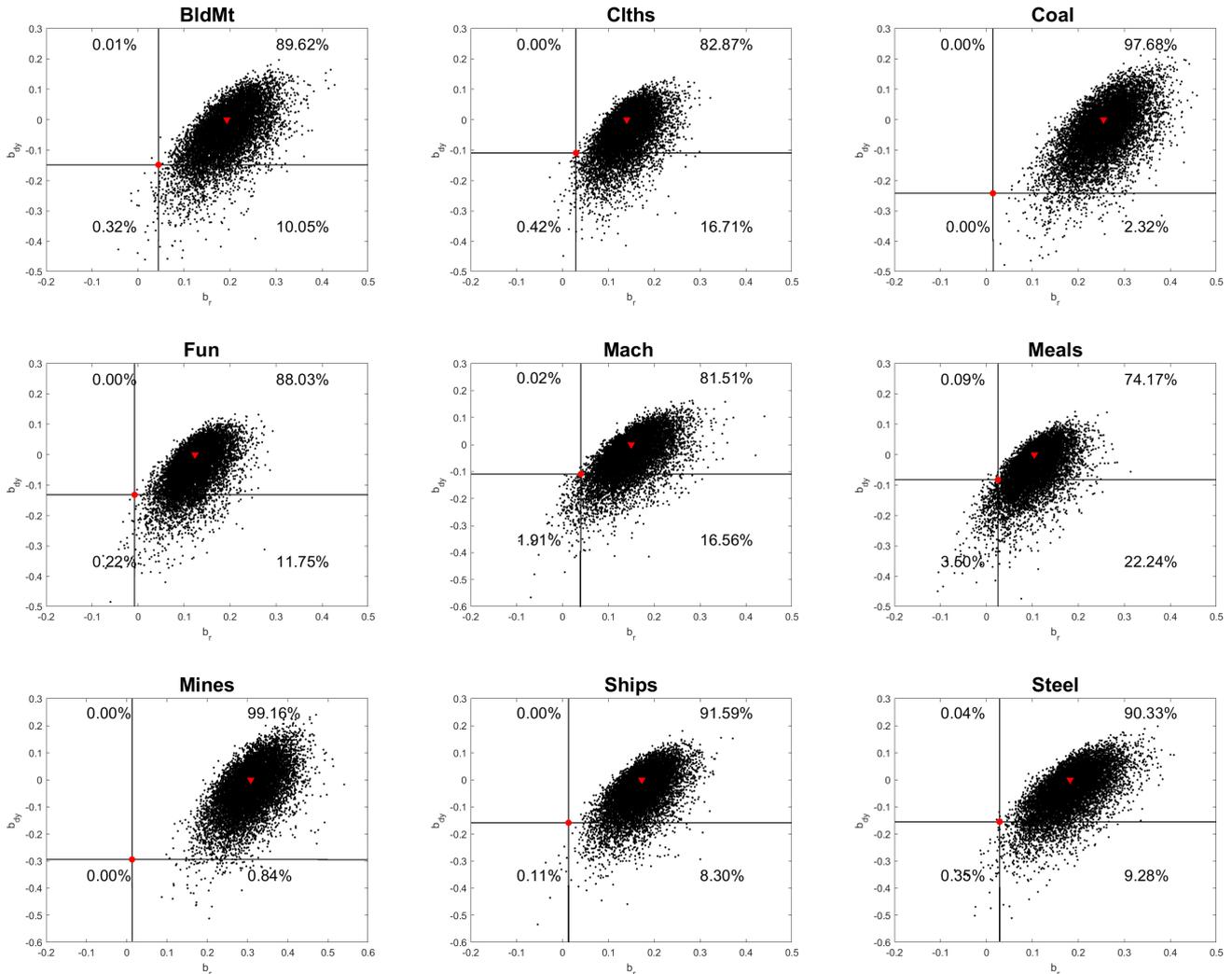


esis of unanticipated returns at the 5% significance level.

However, isolating return predictability is not advisable because, if returns are unpredictable, dividend growth must be predictable. In

Figure 1.2: Joint distribution under the null of no dividend growth predictability

The figure plots joint distribution of simulated predictive coefficients under the null of no dividend growth predictability. Small dots show simulation while large dots show sample estimates. The triangle gives the null. The percentage in each quadrant is the fraction of 10,000 simulations that falls within the quadrant.



fact, among the stock market and all industries presented in Figure 1.1, less than 5% of the simulated dividend growth coefficients b_d (all dots above the horizontal line in the plot) are larger than the sample estimate. Hence, that dividend growth is predictable is unlikely. Put differently, Figure 1.1 presents overwhelming evidence against the presence of dividend growth predictability than against the presence of return predictability in the stock market and 10 other industries.

On the other hand, Figure 1.2 emphasizes the fact that, across nine industries, up to 25% probabilities of the simulated dividend growth coefficients are smaller than their sample coefficients. As a result, when considering dividend growth predictability itself, we could not always reject the null hypothesis of unforeseeable dividend growth at the 5% significance level. Yet, we can always reject the null of the unpredictable return in those industries. The reason is that the sample return coefficients are always among the lowest 5% quantile of the simulated distribution. In short, Figure 1.2 adds supporting evidence for predictable dividend growth in a few sectors, including coal, machinery, and steel works.

Overall, this section confirms that the US stock market return is predictable. Concurrently, this section establishes a return predictability heterogeneity over US industries. Noticeably, the VAR-based results in Table 1.3 and the simulation-based results in Figures 1.1 and 1.2 are almost exactly but slightly different from the direct regression results in Table 1.2. As previously discussed, because the direct predictive method does not concurrently test statistical significance of predictive return or dividend coefficients, the results from this method do not reflect all implications of the present value identity and, thus, are less powerful. Nevertheless, our findings on the predictability pattern across US industries are mostly robust regardless of the applied method.

1.5 Additional Results

In this section, we investigate the relation between return predictability and market size. Furthermore, we attempt to provide a possible explanation for the different predictive patterns across US industries.

Figure 1.3: Return Predictability and Market Size

The figure plots the average firm size, measured by the log of market capitalization, of each individual industry over time against the VAR-based long-run return predictive coefficients.

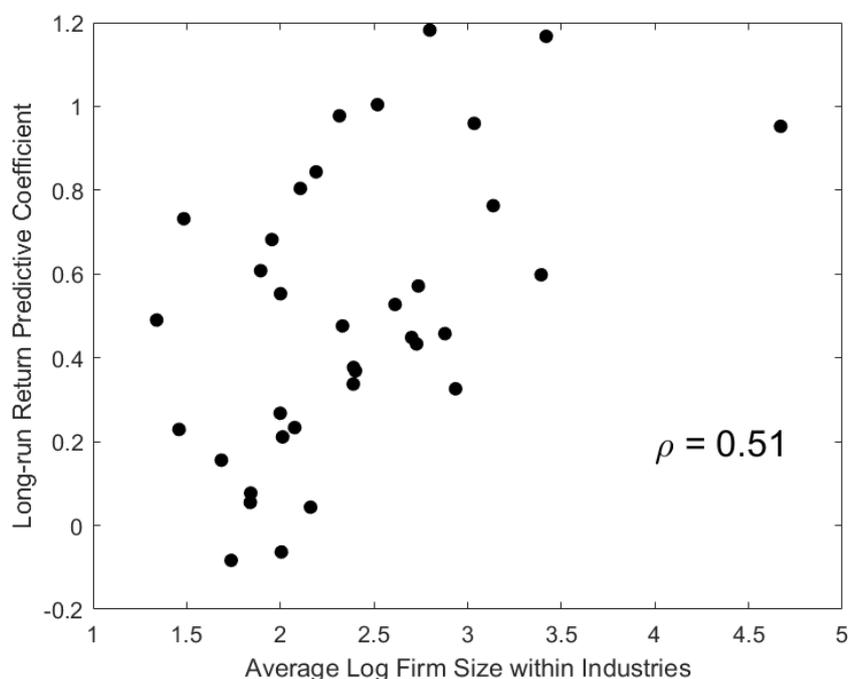


Figure 1.3 plots the average firm size, measured by the log of market capitalization, of each industry over the sample period from 1927 to 2018 against VAR-based long-run return predictive coefficients. Figure 1.3 shows that the long-run return predictive coefficient tends to increase along with an increase in the average firm size within industries. The industries with large average firm or large industries, including tobacco, communication, and petroleum and natural gas, obtain high

return predictive coefficients and vice versa. Moreover, the correlation between two variables is 0.51 and statistically significant, confirming that industries with larger average size firms have more predictable returns. These findings are generally consistent with those of the previous literature concerning the relation between return predictability and market size at the country and stock levels. Specifically, Rangvid et al. (2014) find that stock returns are more predictable in large and developed countries, in which the typical firm is large. Maio and Santa-Clara (2015) confirm that the return predictability pattern is valid for a portfolio of big stocks, not small stocks.

Why are stock returns highly predictable in large industries but less so in smaller sectors? One potential explanation stems from the dividend-smoothing hypothesis inspired by Chen et al. (2012). Using the simulation and portfolio sorting analysis, Chen et al. (2012) demonstrate that a high degree of dividend smoothness makes dividend yields more persistent, which disconnects the link between dividend yield fluctuations and future dividends. As a result, severe dividend smoothing reduces dividend growth predictability but strengthens return predictability. To validate the explanation, we show that dividends tend to be more smoothed in large industries or industries with large average firm by applying the Lintner (1956) modified partial-adjustment model on the equal-weighted (EW) and value-weighted (VW) industry portfolios:

$$\Delta D_t = \beta_0 + \beta_1 \Delta E_t + \beta_2 \Delta D_{t-1} + \varepsilon_t,$$

where ΔD_t and ΔE_t are the annual changes in dividends and earnings. Different from the Lintner's original partial-adjustment model, we include first differences instead of levels of dividends and earnings for the statistical stationarity. In this model, β_2 measures the degree of dividend smoothing. A nonzero β_2 indicates that the variations in past dividends are informative when estimating future dividends or that dividends are smoothed.

Data on dividend payout ratios at the industry level are accessible from the Financial Ratios Suite by WRDS Analytics. Using those ratios, dividends, and the average firm size across industries, we calculate earnings and annual changes in earnings for the EW and VW industry portfolios. The sample period is limited from 1970 to 2018. Table A.1 in Appendix A presents further statistics.

The results of the dividend-smoothing tests are as follows, where the numbers in square brackets are Newey and West (1987) standard errors. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively.

$$\begin{array}{l} \text{EW:} \quad \Delta D_t = 2.40 \quad + 0.02 \Delta E_t - 0.39 \Delta D_{t-1} + \varepsilon_t \quad \overline{R^2} = 25\%, \\ \quad \quad \quad [0.87]^{***} \quad [0.01]^{**} \quad [0.24] \end{array}$$

$$\begin{array}{l} \text{VW:} \quad \Delta D_t = 2.49 \quad + 0.02 \Delta E_t + 0.35 \Delta D_{t-1} + \varepsilon_t \quad \overline{R^2} = 33\%, \\ \quad \quad \quad [1.09]^{**} \quad [0.01]^{**} \quad [0.10]^{***} \end{array}$$

Noticeably, the coefficients of the annual changes in earnings ΔE_t in both the EW and VW portfolios are statistically significant at the 5% level. This suggests that dividends reacts strongly to changes in

earnings over US industries. However, only the smoothing parameter in the VW portfolio is statistically significant. In comparison, future dividends in the EW portfolio fluctuate with noise and do not statistically build on past dividends. Because large industries dominate in the VW portfolio, the evidence further implies that dividends tend to be more smoothed in large sectors.

Chen et al. (2012) propose using the smoothness parameter S as an alternative way to test dividend smoothing:

$$S = \frac{\sigma(\Delta d)}{\sigma(\Delta e)},$$

where $\sigma(\Delta d)$ and $\sigma(\Delta e)$ are the volatility of dividend growth and earnings growth, correspondingly. A smaller value of S means that dividend growth is less volatile than earnings growth, which implies that dividends are more smoothed. The empirical results reveal that the smoothness parameters are 0.260 for the VW portfolio and 0.297 for the EW portfolio, confirming that dividends are more smoothed in sectors in which the average firm is large. This finding complements the study by Leary and Michaely (2011), which identifies that large US firms exhibit more dividend smoothing than small firms.

In summary, this section shows that dividends are more smoothed in large industries. As in the study by Chen et al. (2012), a high degree of dividend smoothness breaks the connection between variations in dividend yields and future dividends, which reduces dividend growth predictability and enhances return predictability. Consequently, stock

returns tend to be predictable in large sectors or in sectors with large average firm, such as tobacco, communication, and petroleum and natural gas, and less so in small sectors, such as coal, steel, and construction materials. These findings support and extend results from other researchers. For example, Chen et al. (2012) find that dividends are smoother in the US post-war sample than the pre-war sample. Thus, there is a reversal of return and dividend predictability during those periods, as addressed by Chen (2009) and Golez and Koudijs (2018). Rangvid et al. (2014) further emphasize that dividends are more smoothed in developed markets, in which the typical firm is large, indicating less dividend growth predictability and more return predictability in those countries.

1.6 Conclusion

This chapter re-examines the pattern of return predictability for the aggregate stock market and investigates whether this pattern is valid across US industries. Using data from the last 91 years, this analysis confirms a classic finding that value-weighted stock returns are predictable in the US setting. Furthermore, this chapter establishes a predictability heterogeneity across US industries, in which stock returns tend to be predictable in large sectors or in sectors with large average firm, such as tobacco, communication, and petroleum and natural gas and less so in small sectors, such as coal, steel, and construction materials. Those findings are generally in line with those of

the previous literature on the relation between return predictability and market size at the country and stock levels. Particularly, Rangvid et al. (2014) find that stock returns are more predictable in countries in which the typical firm is large. Maio and Santa-Clara (2015) further confirm that the return predictability pattern is valid for the portfolio of big stocks, not small stocks.

In addition, this analysis provides a potential explanation for cross-industry predictive patterns. In light of the dividend-smoothing hypothesis, this chapter presents supporting evidence for the higher dividend smoothness in large industries than in small ones. As in the study by Chen et al. (2012), a high degree of dividend smoothness disconnects the link between dividend yield fluctuations and future dividends, which lessens dividend growth predictability and enhances return predictability. Consequently, stock returns are more predictable in large sectors and less so in small sectors. Those findings further suggest that dividend yields are not good proxies for predicting returns in a few small industries.

2

Gold, Platinum, and Industry Stock Returns¹

2.1 Introduction

Stock return predictability has been a topic of interest in the asset pricing literature for a long time. Academics and practitioners establish many works to identify useful factors forming forecasts. In fact, by running regressions of stock returns on numerous observ-

¹This chapter is based on Pham, Quynh T, and Markus Rudolf, 2021, Gold, platinum, and industry stock returns, *International Review of Economics & Finance* 75, 252–266, presented at the 34th Austrian Working Group (AWG) Workshop on Banking and Finance, 2019.

able or implied variables, a large number of studies document various predictors anticipating stock returns. These predictors mainly belong to two categories: financial ratios and business cycle indicators. The former category includes dividend yields, the price-earnings ratio, the book-to-market ratio, and the dividend payout ratio (See, e.g. Fama and French (1988), Kothari and Shanken (1997), Lamont (1998), and Lewellen (2004)). The latter category involves the default spread, the term spread, the consumption-wealth ratio, the output gap, and the ratio of gold to platinum prices (See, e.g., Fama and French (1989), Lettau and Ludvigson (2001), Cooper and Priestley (2008), Della Corte, Sarno, and Valente (2010), Vivian and Wohar (2013), and Huang and Kilic (2019)).

In a recent paper, Huang and Kilic (2019) find that the ratio of gold to platinum prices (GP) can predict short- and medium-term market stock returns. According to Huang and Kilic (2019), gold and platinum can be viewed either as commodity goods, mostly in the form of jewelry, or store-of-value assets. In normal times, because investors are more willing to pay for jewelry when they are relatively rich, both gold and platinum are highly valuable. However, when investors expect a consumption shock, they would prefer spending money on food rather than jewelry, gold and platinum prices decrease. Since gold offers greater counter-cyclical benefits than platinum, gold prices decrease less than platinum prices. Consequently, GP is high in bad states of the economy.

Likewise, market stock returns correlate with business cycles. Typ-

ically, stock prices increase in expansions and decrease in recessions. Due to this fact, investors would expect a higher premium to compensate themselves for holding risky assets that fall in bad times. Expected stock returns increase in recessions and so does GP, providing GP with the ability to predict stock returns.

This chapter extends the work of Huang and Kilic (2019) to the industry level. If indeed GP can capture the business cycle risk of stock returns, GP should predict cross-cyclical industry returns. Therefore, we investigate whether GP leads US industry stock returns in-sample over short and intermediate horizons. Motivated by the research of Campbell and Thompson (2008), we also test unconstrained and constrained out-of-sample return predictability by GP. In addition, by comparing the out-of-sample performance of a GP-based with the passive buy-and-hold trading strategy, we evaluate economic significance of GP forecasts. Addressing these aspects is essential to gain better understanding of the channel driving GP predictive power and assist investors in their cross-industry investment decisions.

Our work relates to the growing literature that examines return predictability at the industry level (See, e.g., Beller et al. (1998), Lewellen (1999), Fan and Jahan-Parvar (2012), Phan, Sharma, and Narayan (2015), Da, Huang, and Yun (2017), Chiang and Hughen (2017), Valcarcel, Vivian, and Wohar (2017), and Salisu, Raheem, and Ndako (2019)). Different from the existing studies, we choose GP as a potential predictor for industry stock returns because of many reasons. First, unlike other financial ratios, GP does not incorporate any forms

of asset prices. Therefore, using GP as one of non-financial-based variables removes predictability bias arising due to fads in prices being canceled out (Cochrane (2005b)). Second, although being successful in forecasting returns at long horizons, commonly used financial ratios exhibit little explanatory power over short horizons (Lettau and Ludvigson (2001)). Meanwhile, business cycle indicators are able to shift the term structure of expected returns, thus, predict returns more precisely over business cycles. Given that the chapter focuses on short- and intermediate-horizon predictability, selecting GP as the predictor is advantageous. Third, contrary to other market-based variables, GP is a high-frequency and model-free ratio, which is useful for forming forecasts, especially in real-time trading.

In this chapter, we identify the cyclicity of a particular industry based on its return correlation with market returns. Using monthly data from 1975 to 2019, we find that GP forecasts cyclical industry excess returns better than defensive industry excess returns. Given that GP exhibits power to capture cyclical components of stock returns, the ability of GP in forecasting one industry is broadly sensitive to cyclical risk exposure of that industry. Because cyclical industry stock returns highly vary with business cycles, GP can track these cyclical industry returns. This finding remains robust to several robustness checks, such as subsample analysis, alternative econometric method, and alternative classification of industry cyclicity, proposed by Boudoukh, Richardson, and Whitelaw (1994). Also, we show that the out-of-sample forecast by GP is weak, nevertheless economically

meaningful for mean-variance investors. As an illustration, a GP-based one-month trading strategy outperforms the passive strategy in various sectors. On average, the GP-based strategy generates an annualized certainty equivalent return that is approximately 2.4% higher than the buy-and-hold strategy across all sectors.

2.2 Data

2.2.1 US industry-level returns

Dependent variables in this analysis are market and 49 industry² excess returns. We collect monthly value-weighted (VW) returns from 1975 to 2019 from [Kenneth R. French's data library](#). Market returns are returns of all CRSP US firms listed on the NYSE, AMEX, or NASDAQ with the share code of 10 or 11. Industry-level returns are returns of US firms incorporated in the industry that corresponds to

²The industries are Aircraft (Aero), Agriculture (Agric), Automobiles and Trucks (Autos), Banking (Banking), Beer and Liquor (Beer), Construction Materials (BldMt), Printing and Publishing (Books), Shipping Containers (Boxes), Business Services (BusSv), Chemicals (Chems), Electronic Equipment (Chips), Apparel (Clths), Construction (Cnstr), Coal (Coal), Pharmaceutical Products (Drugs), Electrical Equipment (ElcEq), Fabricated Products (FabPr), Trading (Fin), Food Products (Food), Entertainment (Fun), Precious Metals (Gold), Defense (Guns), Computers (Hardw), Healthcare (Hlth), Consumer Goods (Hshld), Insurance (Insur), Measuring and Control Equipment (LabEq), Machinery (Mach), Restaurants, Hotels, and Motels (Meals), Medical Equipment (MedEq), Non-Metallic and Industrial Metal Mining (Mines), Petroleum and Natural Gas (Oil), Business Supplies (Paper), Personal Services (PerSv), Real Estate (REst), Retail (Rtail), Rubber and Plastic Products (Rubbr), Shipbuilding and Railroad Equipment (Ships), Tobacco Products (Smoke), Candy and Soda (Soda), Computer Software (Softw), Steel Works etc. (Steel), Communication (Telcm), Recreation (Toys), Transportation (Trans), Textiles (Txtls), Utilities (Util), and Wholesale (Whlsl).

Table 2.1: Descriptive statistics of industry excess returns

The table presents the descriptive statistics of the annualized log VW excess returns for the market and 49 industries. ADF denotes Augmented Dickey Fuller t-statistics. The sample period is from 1975 to 2019.

Industry	Mean	St. Dev.	Skew.	Kurt.	Min	Max	AR(1)	ADF
Market	0.07	0.53	-0.98	3.40	-3.15	1.40	0.06	-21.50
Aero	0.10	0.78	-0.95	4.09	-4.39	2.61	0.09	-20.81
Agric	0.06	0.74	-0.45	3.12	-4.19	2.99	-0.02	-23.35
Autos	0.04	0.84	-0.58	6.10	-5.44	4.83	0.10	-20.80
Banks	0.07	0.72	-0.92	3.27	-3.82	2.16	0.10	-20.75
Beer	0.09	0.60	-0.47	2.40	-2.69	2.34	-0.03	-23.36
BldMt	0.07	0.74	-0.81	5.27	-4.41	3.65	0.06	-21.53
Books	0.06	0.67	-0.32	2.75	-3.49	3.22	0.13	-20.32
Boxes	0.07	0.69	-0.84	3.35	-4.05	2.14	0.02	-22.65
BusSv	0.08	0.65	-1.09	4.41	-3.96	1.94	0.09	-21.00
Chems	0.06	0.68	-0.57	3.47	-4.01	2.35	0.04	-22.05
Chips	0.08	0.91	-0.94	3.35	-4.71	2.84	0.04	-22.18
Clths	0.09	0.76	-0.65	3.61	-4.51	2.63	0.14	-19.77
Cnstr	0.06	0.85	-0.59	2.36	-4.54	2.51	0.12	-20.50
Coal	-0.01	1.31	-0.50	2.07	-5.74	4.32	0.08	-21.33
Drugs	0.08	0.58	-0.37	0.96	-2.62	1.76	-0.03	-23.72
ElcEq	0.09	0.76	-0.74	3.62	-4.74	2.50	-0.01	-23.10
FabPr	0.03	0.86	-0.50	1.92	-3.79	3.18	0.10	-21.04
Fin	0.08	0.74	-0.84	2.69	-3.65	2.14	0.14	-19.94
Food	0.09	0.51	-0.30	2.15	-2.44	2.07	0.01	-22.40
Fun	0.10	0.89	-0.84	3.95	-4.68	3.93	0.13	-20.30
Gold	0.00	1.29	0.08	2.00	-4.92	6.91	-0.04	-24.10
Guns	0.10	0.76	-0.90	4.31	-4.34	3.30	0.04	-21.82
Hardw	0.05	0.88	-0.68	3.00	-4.94	2.67	0.04	-22.24
Hlth	0.09	0.84	-0.61	2.64	-4.60	2.71	0.11	-20.68
Hshld	0.06	0.54	-0.60	2.61	-3.00	2.00	0.05	-21.87
Insur	0.08	0.63	-0.90	3.53	-3.70	2.42	0.08	-20.97
LabEq	0.07	0.83	-0.56	2.22	-4.38	2.28	0.07	-21.64
Mach	0.06	0.78	-1.00	4.39	-4.56	2.49	0.07	-21.53
Meals	0.09	0.64	-0.84	2.87	-3.37	1.72	0.13	-20.08
MedEq	0.08	0.62	-0.77	2.10	-2.83	1.77	0.04	-22.00
Mines	0.04	0.94	-0.83	3.74	-5.13	2.86	0.04	-22.12
Oil	0.06	0.67	-0.32	1.17	-2.50	2.53	-0.01	-23.20
Other	0.03	0.75	-0.86	2.98	-3.76	2.20	0.06	-21.73
Paper	0.07	0.65	-0.37	3.43	-3.74	2.56	0.01	-22.68
PerSv	0.05	0.72	-0.64	2.69	-4.06	2.58	0.04	-22.23
REst	0.02	0.88	-0.64	10.27	-6.02	6.31	0.20	-18.86
Rtail	0.08	0.64	-0.72	3.67	-4.21	1.82	0.11	-20.52
Rubbr	0.08	0.70	-0.82	4.85	-4.45	3.33	0.07	-21.43
Ships	0.06	0.89	-0.54	2.52	-4.75	3.07	0.05	-21.88
Smoke	0.10	0.75	-0.63	2.98	-3.49	3.36	0.03	-21.97
Soda	0.08	0.75	-0.31	3.49	-3.66	3.85	0.03	-22.21
Softw	0.10	1.02	-0.11	1.55	-3.98	4.06	0.03	-22.16
Steel	0.01	0.95	-0.72	3.27	-4.80	3.17	0.05	-22.00
Telecm	0.06	0.57	-0.55	1.58	-2.15	2.31	0.04	-21.93
Toys	0.05	0.82	-0.70	3.11	-5.13	2.46	0.07	-21.53
Trans	0.07	0.66	-0.80	3.11	-4.00	1.92	0.06	-21.54
Txtls	0.06	0.89	-0.63	7.49	-4.79	5.57	0.14	-19.97
Util	0.07	0.46	-0.51	0.88	-1.62	1.27	0.01	-22.44
Whlsl	0.07	0.61	-0.97	5.24	-4.12	1.93	0.10	-20.84

four-digit Standard Industrial Classification (SIC) codes. To construct excess returns, we use the one-month Treasury-bill rate from Ibbotson Associates as a proxy for the risk-free rate.

Table 2.1 presents the descriptive statistics of the annualized log VW excess returns for the market and 49 industries. As in Table 2.1, most industry excess returns vary between 4% and 10%. A few of industries, such as steel works, fabricated products (FabPr), coal, and precious metals (Gold), yield lower or even negative excess returns. These sectors also hold among the highest return volatility. All industry excess returns obtain negative skewness (skew to the left) with excessive positive kurtosis. In addition, all data are less persistent and stationary. These features are common for stock excess returns.

2.2.2 GP and other predictor variables

We obtain monthly average a.m. gold and platinum prices, quoted in USD per fine ounce, from the [London Bullion Market Association](#). Platinum prices are available from April 1990. For the preceding data, we use platinum dealer prices from the [US Geological Survey](#). GP is the natural logarithm of the gold to platinum price ratio.

Following Huang and Kilic (2019), this chapter focuses exclusively on the post-gold standard era, in which gold prices are determined freely by the market. In addition, our sample excludes the period of the Oil Shock, from November 1973 to March 1975. This exclusion is important because, as Welch and Goyal (2008) address, a large amount of statistical significance bias stems from data that include

the Oil Shock period. The final sample period is from January 1975 to December 2019.

To compare the predictive ability of GP with other known predictors, we also gather data of a few variables as follows. All data, unless stated otherwise, are monthly data spanning from 1975 to 2019.

- The price-dividend ratio (log PD), the cyclically adjusted price-earnings ratio (log PE), and the dividend payout ratio (log DE) are from [Robert J. Shiller's website](#).
- The book-to-market-ratio (BM) is from [Amit Goyal's website](#), available until 2018.
- The default spread (Default), in percentage points, is the difference between yields on BAA and AAA Moody's Corporate Bonds. The term spread (Term), in percentage points, is the difference between 10-year and 3-month Treasury yields, available from 1982. These data are from the Federal Reserve Bank of St. Louis (FRED).
- The consumption-wealth ratio (CAY) is from [Martin Lettau's website](#). Data are quarterly data available until 2018, which are interpolated to a monthly frequency.
- The output gap (Output) is the residual deriving from the regression of the log industrial production on a time trend and a quadratic time trend. The industrial production data are from FRED.

Table 2.2 presents the descriptive statistics of GP and the alter-

Table 2.2: Descriptive statistics of predictors

The table presents the descriptive statistics of GP and the alternative predictors, which are the price-dividend ratio (log PD), the cyclically adjusted price-earnings ratio (log PE), the dividend payout ratio (log DE), the book-to-market-ratio (BM), the default spread (Default), the term spread (Term), the consumption-wealth ratio (CAY), and the output gap (Output). ADF denotes Augmented Dickey Fuller t-statistics. The lag length in the ADF test is selected using the Schwarz Information Criterion (SIC). ***, **, and * indicate the ADF test rejects the null hypothesis of a unit root at the 1%, 5%, and 10% significance level, respectively.

Predictors	Mean	St. Dev.	AR(1)	ADF	Min	Max	Corr. GP
GP	-0.172	0.301	0.989	-1.935	-0.850	0.555	1.000
log PD	3.662	0.433	0.997	-1.443	2.775	4.502	-0.354
log PE	2.864	0.473	0.992	-2.883**	1.915	4.818	-0.206
log DE	-0.798	0.334	0.985	-4.219***	-1.244	1.380	0.166
BM	0.458	0.280	0.996	-1.739	0.121	1.207	0.278
Default	1.096	0.455	0.965	-3.757***	0.550	3.380	0.191
Term	1.777	1.111	0.969	-3.303**	-0.700	4.150	0.073
CAY	0.004	0.022	0.995	-1.577	-0.041	0.040	-0.180
Output	0.000	0.060	0.994	-2.486	-0.124	0.121	-0.571

native predictors. In general, the statistics are in line with those indicated in prior studies. First, GP and all other variables are quite persistent with the first-order autocorrelations ranging from 0.965 to 0.997. According to Stambaugh (1999), highly persistent regressors increase the finite-sample bias in predictive regressions. Lewellen (2004) suggests using the conditional approach to minimize the bias, given that the predictor autocorrelation is close to one.

Second, the Augmented Dickey Fuller test fails to reject the null of a unit root in GP at the 5% level. However, in the unreported results, the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test fails to reject the null hypothesis of stationary GP, leading to mixed results in GP stationarity tests. Because strong evidence for the cointegration between gold and platinum prices exists, assuming GP to be at least weakly stationary is reasonable.

Third, Table 2.2 presents that GP moderately correlates with many predictors whereas correlates with the output gap to the greatest extent. This result is not surprising because both GP and the output gap are highly sensitive to and vary with business cycles.

2.3 In-sample predictability

This section presents the in-sample predictability results. Formally, we use Equation (2.1) to test the in-sample predictive ability of GP and other predictors.

$$\frac{12}{h} \sum_{i=1}^h \left[\log R_{t+i} - \log R_{t+i}^f \right] = \beta_0 + \beta_1 X_t + \varepsilon_{t+h}, \quad (2.1)$$

where R_t is the stock return, R_t^f is the risk-free rate, X_t can be GP_t or other predictors, h is the horizon length in months, and ε_t is the error term. In general, GP_t is a good excess return predictor if the estimate of β_1 is statistically positive.

2.3.1 Short-term forecasts

At the one-month horizon, Stambaugh (1999) emphasizes that a high degree of the regressor autocorrelation potentially violates the assumption for an unbiased OLS, which induces unreliable statistical inference in predictive regressions. To address this issue, we apply the conditional approach suggested by Lewellen (2004). The conditional method, however, requires a monthly predictor autocorrelation around 0.98 and 0.99 with 20 years and 50 years of data, correspondingly. Be-

Table 2.3: Short-term forecasts by GP and others predictors

This table presents the coefficient β_1 of the one-month conditional predictive regression using GP and other predictors. ***, **, and * indicate significant coefficients at the one-sided 1%, 5%, and 10% level, respectively. The sample period is from January 1975 to December 2019.

Industry	GP	log PD	log PE	log DE	BM	Default	Term	CAY	Output
Market	0.194***	-0.062**	-0.040	0.024	0.062	0.016	0.006	0.169	-0.799**
Aero	0.211**	-0.096*	-0.086	-0.012	0.155	0.016	0.017	-1.252	-0.677
Agric	-0.003	-0.037	-0.096*	-0.131	0.063	-0.003	-0.021	0.414	0.178
Autos	0.289***	-0.112**	0.017	0.222	0.111	0.136	0.027	0.024	-1.834***
Banks	0.229***	-0.041	-0.019	0.031	0.027	-0.065	0.019	1.384	-1.082**
Beer	0.163***	-0.102**	-0.063	0.046	0.079	0.059	-0.002	1.678**	-1.119***
BldMt	0.165**	-0.09*	-0.038	0.074	0.099	0.070	0.040*	0.229	-1.207***
Books	0.244***	-0.139***	-0.068	0.096	0.221***	0.088	0.041*	0.066	-1.01**
Boxes	0.120*	-0.091*	-0.021	0.112	0.068	0.123*	0.023	0.810	-1.147***
BusSv	0.251***	-0.115***	-0.100	-0.007	0.164**	0.057	0.003	-1.060	-0.771**
Chems	0.095	-0.058	-0.002	0.091	0.030	0.053	0.019	0.435	-1.169***
Chips	0.421***	-0.104	-0.032	0.110	0.113	0.031	0.026	-0.926	-1.250*
Clths	0.170**	-0.118**	-0.068	0.062	0.190**	0.138*	0.017	-0.911	-1.005**
Cnstr	0.042	-0.020	-0.047	-0.059	0.072	0.042	-0.007	-0.901	0.138
Coal	-0.448	0.095	0.107	0.056	-0.125	0.002	-0.076	1.635	1.230
Drugs	0.149**	-0.042	-0.056	-0.041	0.005	-0.021	-0.031	1.452*	-0.560*
ElcEq	0.195**	-0.067*	-0.035	0.042	0.069	0.039	0.003	1.000	-0.723*
FabPr	0.108	-0.099	-0.064	0.037	0.067	0.016	0.025	-0.811	-0.794*
Fin	0.215**	-0.072*	-0.009	0.103	0.070	0.022	0.002	0.645	-0.691
Food	0.083*	-0.088**	-0.071	0.005	0.082*	0.056	0.014	1.783**	-0.952***
Fun	0.229**	-0.105*	-0.046	0.085	0.151	0.006	0.031	-1.414	-0.904*
Gold	-0.007	-0.076	0.026	0.181**	0.126	0.248**	0.049	-1.207	-0.519
Guns	0.076	-0.048	-0.092	-0.103	0.118	-0.003	0.008	-1.695	-0.287
Hardw	0.309**	-0.053	0.013	0.116	0.033	0.066	0.010	-0.161	-0.816
Hlth	0.095	-0.199**	-0.196*	-0.058	0.376***	0.089	-0.002	-2.547	0.018
Hshld	0.135**	-0.024	0.002	0.044	-0.001	0.028	0.014	1.330*	-0.896***
Insur	0.175**	-0.058	-0.058	-0.019	0.080	-0.039	0.018	-0.405	-0.616*
LabEq	0.268**	-0.083	-0.057	0.024	0.119	0.068	0.006	-1.791	-0.840*
Mach	0.119*	-0.004	0.025	0.057	-0.021	0.005	0.006	-0.695	-0.647*
Meals	0.165**	-0.082*	-0.059	0.018	0.119	0.080	0.023	-0.921	-0.892**
MedEq	0.134**	-0.004	-0.007	-0.008	-0.014	-0.002	-0.028	-0.326	-0.455
Mines	-0.080	0.005	0.082	0.157	-0.039	0.061	-0.020	0.176	-0.283
Oil	-0.109	-0.021	-0.055	-0.074	0.036	-0.047	-0.012	0.502	0.159
Other	0.161**	-0.138***	-0.156	-0.082	0.213***	0.014	-0.014	-1.125	-0.668
Paper	0.139**	-0.075*	-0.003	0.119	0.077	0.087	0.032	0.276	-1.150***
PerSv	0.098	-0.129**	-0.096	0.025	0.188**	0.071	0.039*	-0.606	-0.616*
REst	0.125	-0.118*	-0.045	0.108	0.214*	0.081	0.069*	-2.089	-0.793
Rtail	0.221***	-0.061*	-0.025	0.053	0.066	0.103*	0.003	0.188	-1.101***
Rubbr	0.190**	-0.093*	-0.026	0.104	0.095	0.073	0.029	-0.082	-1.282***
Ships	-0.008	0.042	0.000	-0.070	0.020	-0.011	0.020	-3.047	-0.019
Smoke	-0.123	-0.042	-0.074	-0.077	0.066	0.036	-0.026	0.992	-0.321
Soda	0.179**	-0.052	0.008	0.103	0.032	0.083	0.024	1.024	-1.056**
Softw	0.341***	-0.163**	-0.083	0.108	0.179	0.081	0.004	-0.446	-1.027*
Steel	0.085	-0.035	-0.013	0.031	0.010	0.010	0.003	-0.009	-0.576
Telcm	0.259***	-0.096**	-0.081	-0.002	0.094	0.018	0.007	0.610	-1.018**
Toys	0.191**	-0.133**	-0.050	0.123	0.163	0.142*	0.031	0.420	-1.618***
Trans	0.109*	-0.071*	-0.053	0.013	0.083	0.034	0.029	-0.243	-0.933**
Txtls	0.118	-0.157**	-0.068	0.127	0.216**	0.116	0.058*	-0.462	-1.550***
Util	0.038	-0.012	-0.050	-0.080	0.033	-0.023	-0.005	-0.052	-0.288
Whsl	0.163**	-0.118***	-0.082	0.033	0.187***	0.109	0.026	-0.566	-0.809**

cause most predictors, except the default and term spread, satisfy the autocorrelation benchmark for the conditional approach, we run the conditional predictive regression for the one-month horizon as follows:

$$\log R_{t+1} - \log R_{t+1}^f = \beta_0 + \beta_1 X_t + \gamma \mu_t + \nu_t,$$

where μ_t is the residual of the regression $X_{t+1} = \phi + \rho X_t + \mu_t$ and ν_t is the error term.

Table 2.3 presents the one-month predictive results by GP and other variables, using the conditional approach to correct the finite-sample bias. In all regressions, we calculate t-statistics using Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors. The sample period is from January 1975 to December 2019.

The second column of Table 2.3 presents one-month excess return forecasts by GP. At the market level, GP strongly predicts excess returns, confirming the finding of Huang and Kilic (2019). The estimated coefficient is positive and statistically significant at the 1% level, implying that a decrease in GP this month is associated with a lower next-month excess return. Economically, a 1% decrease in GP this month leads to a 0.194% decrease in the next month's excess return.

At the industry level, 28 and 32 out of 49 GP predictive coefficients are statistically positive at the 5% and 10% level, respectively. The GP ability in predicting one-month industry excess returns is not that

impressive, yet economically meaningful. On the one hand, because one-month excess returns are highly volatile, even small return forecast power could generate a large profit, especially for mean-variance investors. On the other hand, GP outperforms many commonly used variables, including the price-dividend ratio and the consumption-wealth ratio, in determining one-month excess returns. In addition, GP performs as well as the output gap; although contrary to the output gap, GP is a model-free and forward-bias-free variable.

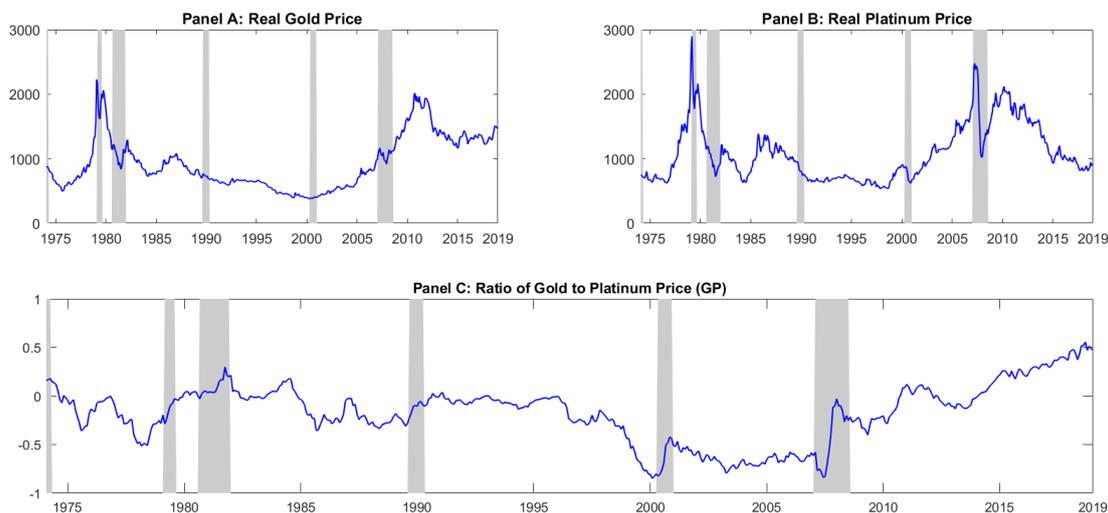
Noticeably, most GP predictive coefficients across industries are positive, indicating that investors would expect a fall in industry stock returns once they observe an increase in GP. Only few exceptions related to energy and metal sectors, such as non-metallic and industrial metal mining (Mines), petroleum and natural gas (Oil), and coal, are associated with negative predictive slopes. This fact raises an interesting question of which channel driving the different GP predictive power across industries. The next section attempts to address this question.

2.3.2 Channel of GP predictive ability

In the recent study, Huang and Kilic (2019) explain reasons behind the predictive power of GP on stock market returns. According to Huang and Kilic (2019), gold and platinum can exist in two states, either as commodity goods, mostly in the form of jewelry, or as store-of-value assets. In normal times, because utility from wearing jewelry increases when investors are relatively rich, both gold and platinum are highly

Figure 2.1: Gold, Platinum, and GP over business cycles

The figure demonstrates real gold prices, real platinum prices (USD per fine ounce), and GP over business cycles from 1975 to 2019. The base month is 2019M12. The real gold and platinum prices are calculated using monthly data of the Consumer Price Index (CPI): All Items for the US, accessible from FRED. The shaded grey bars indicate recession periods defined by the National Bureau of Economic Research (NBER).



valuable. However, in periods of high uncertainty or in recessions, investors would prefer spending money on food rather than jewelry, gold and platinum prices fall. Since gold offers greater countercyclical benefits than platinum, gold prices fall less than platinum prices. Thus, GP is high in bad states of the economy. Figure 2.1 plots the behavior of real gold prices, real platinum prices, and GP over business cycles. Consistent with the mentioned explanation, Panel A and B reveal that both real gold and platinum prices tend to decline in recessions, although gold prices decrease less than platinum prices. Meanwhile, GP increases rapidly in recessions (Panel C).

Similarly, market stock returns also correlate with business cycles. In most cases, stock prices increase in expansions and decrease in recessions. Due to this fact, investors would expect a higher stock

return to compensate themselves for holding risky assets that fall in bad times. Expected stock returns increase in recessions; and so does GP, providing GP with the ability to predict stock returns.

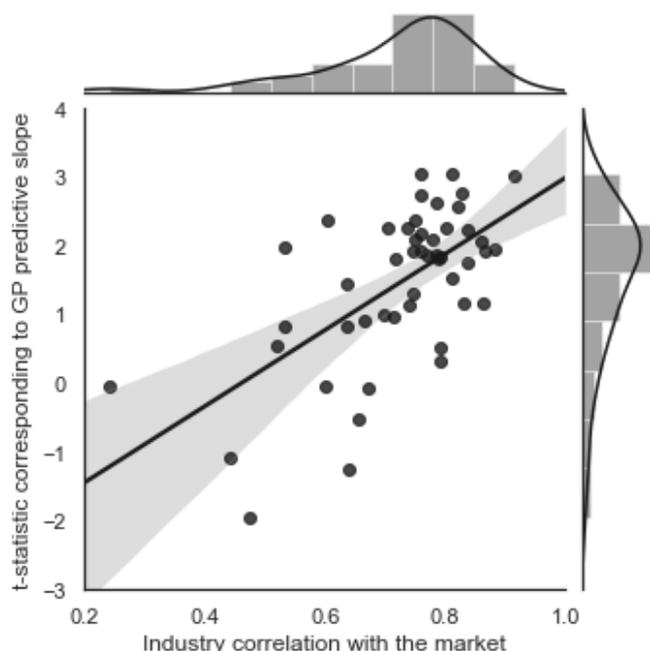
Given that GP demonstrates power to capture cyclical components of stock returns, the ability of GP in forecasting one industry is broadly sensitive to cyclical risk exposure of that industry. At an intuitive level, we hypothesize that GP forecasts positively cyclical industry stock returns, whereas it exhibits limited ability to lead noncyclical or defensive sectors.

By definition, a cyclical industry is an industry whose performance is highly correlated to business cycles. Empirically, we categorize cyclical and defensive industries based on their return correlation with the market. Cyclical and defensive industries hold the correlation with market returns (the industry cyclical proxy) close to one and null, respectively. To obtain a proxy that allows us to conduct a detailed cross-industry analysis, we choose industry return as our measure of industry performance. According to this proxy, top five cyclical industries are business services (BusSv), trading (Fin), electrical equipment (ElcEq), machinery (Mach), and wholesale, whereas the top five defensive industries are precious metals (Gold), tobacco products (Smoke), coal, utilities, and defense (Guns). These industries are typical cyclical and defensive industries in nature.

Figure 2.2 plots the industry cyclical proxy against t-statistics corresponding to GP predictive slopes in 49 sectors. Figure 2.2 demonstrates that t-statistics tend to increase when the industry correlation

Figure 2.2: Market correlation and industry return forecasts by GP

The figure plots the industry correlation with the market return (the industry cyclicity proxy) against t-statistics corresponding to GP predictive slopes in 49 industries.



with the market return increases. Cyclical industries, such as business services, trading, and electrical equipment obtain higher t-statistics. Conversely, defensive industries, including precious metals, tobacco products, and utilities, receive lower t-statistics. To test this link, we regress t-statistics corresponding to GP predictive slopes on the industry cyclicity proxy. The coefficient from this regression equals 5.81 (with the Newey and West (1987) corrected t-value of 4.62 and \bar{R}^2 of 39%). The evidence implies a positive and statistically significant relation between two variables and that GP forecasts cyclical better than defensive industries.

2.3.3 Medium-term forecasts

Can GP provide the valuable information for industry excess returns over intermediate horizons? Table 2.4 summarizes results of three-month, one-year, and five-year market and 49 industry excess return regressions on GP. Instead, of sorting industries by name, Table 2.4 sorts industries by their correlation with market returns, which is presented in the last column. Based on Newey and West (1987) corrected t-statistics, ***, **, and * indicate positive coefficients at the one-sided 1%, 5%, and 10% significance level, respectively. The sample period is from January 1975 to December 2019.

To start with, we examine the market forecast by GP over intermediate horizons. Consistent with the one-month regression result, Table 2.4 presents a strong market excess return forecast by GP. For all horizons from three months to five years, the estimated coefficients are positive and statistically significant at the 1% level. Although the magnitude of GP predictive slope reduces at the five-year horizon, the \bar{R}^2 increases continuously with forecasting horizons. In particular, the \bar{R}^2 demonstrates that GP justifies 3.37%, 14.47%, and 28.8% of the future three-month, one-, and five-year market excess returns, correspondingly.

The regression results for cyclical industries in the upper part of Table 2.4 reveal a similar pattern. For almost all of cyclical sectors, such as business services (BusSv), trading (Fin), and wholesale, GP predictive slopes are positive and significant. These slopes increase

Table 2.4: Medium-term forecasts by GP

The table shows medium-term GP forecast for the excess market and industry returns. The sample period is from January 1975 to December 2019.

Industry	3-month horizon		1-year horizon		5-year horizon		Corr. Mkt
	Coef.	R_{adj}^2 (%)	Coef.	R_{adj}^2 (%)	Coef.	R_{adj}^2 (%)	
Market	0.198***	3.37	0.206***	14.47	0.125***	28.80	1.000
BusSv	0.251***	3.54	0.249***	14.87	0.142***	25.52	0.915
Fin	0.237**	2.17	0.256***	10.17	0.190***	30.99	0.884
ElcEq	0.199**	1.73	0.181**	6.86	0.092***	11.45	0.866
Mach	0.139	0.59	0.117	2.29	0.014	0.12	0.865
Whsl	0.176**	1.78	0.175***	8.28	0.074***	10.63	0.859
BldMt	0.171*	1.15	0.165**	5.33	0.095***	11.80	0.839
LabEq	0.273**	2.54	0.243***	8.70	0.075**	5.36	0.838
Chems	0.11	0.48	0.113	2.71	0.034*	1.73	0.831
Chips	0.430***	5.51	0.382***	14.47	0.207***	20.64	0.827
Books	0.256***	3.19	0.290***	14.73	0.277***	48.89	0.820
Rtail	0.226***	2.89	0.210***	12.68	0.113***	20.28	0.811
Trans	0.119*	0.63	0.153***	6.27	0.048***	4.80	0.810
Rubbr	0.195**	1.73	0.202***	9.97	0.099***	15.92	0.802
Paper	0.139*	1.05	0.173***	7.93	0.115***	23.28	0.792
Cnstr	0.05	-0.11	0.006	-0.18	0.056	2.47	0.791
Steel	0.116	0.19	0.122	1.33	0.04	1.29	0.791
Other	0.173*	1.16	0.221***	8.36	0.175***	25.47	0.788
Banks	0.241***	2.49	0.303***	16.11	0.247***	41.92	0.785
Fun	0.244*	1.60	0.258**	7.99	0.164***	27.95	0.785
Insur	0.191**	2.16	0.241***	13.65	0.189***	42.89	0.777
Hardw	0.324**	3.22	0.316***	9.89	0.099**	5.03	0.770
Telcm	0.268***	5.55	0.296***	18.29	0.177***	24.94	0.761
MedEq	0.144**	1.18	0.139***	4.66	0.103***	19.71	0.761
Aero	0.230**	1.96	0.226***	8.66	0.084***	8.26	0.760
Softw	0.324***	2.52	0.266***	6.81	0.156***	11.26	0.759
Meals	0.156**	1.22	0.134***	5.05	0.002	-0.20	0.751
Autos	0.311**	3.08	0.313***	12.00	0.190***	31.81	0.749
Clths	0.174**	1.04	0.140**	3.47	0.006	-0.14	0.748
Boxes	0.128	0.71	0.079	1.26	-0.011	-0.04	0.748
PerSv	0.084	0.18	0.106*	2.51	0.069**	7.06	0.740
Hshld	0.127**	1.25	0.143***	8.22	0.066***	9.95	0.738
Toys	0.201**	1.36	0.184***	5.64	0.049	2.18	0.716
REst	0.145	0.40	0.145	1.87	0.027	0.15	0.716
Drugs	0.140***	1.44	0.168***	8.02	0.171***	30.91	0.703
Txtls	0.165	0.63	0.172	3.15	0.122***	8.71	0.697
Ships	0.007	-0.19	0.032	-0.04	-0.055	1.19	0.671
FabPr	0.127	0.32	0.147*	2.84	-0.023	0.30	0.666
Mines	-0.078	-0.02	-0.144	1.98	-0.183	21.68	0.655
Oil	-0.102	0.45	-0.082	1.47	-0.029	1.42	0.639
Food	0.086	0.56	0.113**	4.60	0.113***	18.65	0.635
Hlth	0.091	0.10	0.064	0.35	0.055	1.59	0.635
Beer	0.154**	1.73	0.162***	8.65	0.132***	20.38	0.603
Agric	-0.012	-0.18	-0.018	-0.12	-0.01	-0.02	0.601
Soda	0.192**	1.62	0.168***	5.53	0.058**	3.33	0.534
Guns	0.08	0.11	0.083	0.98	0.063**	3.53	0.532
Util	0.044	0.06	0.088	3.33	0.033**	4.24	0.519
Coal	-0.388	1.76	-0.301	4.10	-0.233	9.70	0.474
Smoke	-0.138	0.68	-0.099	1.55	-0.021	0.32	0.444
Gold	-0.067	-0.11	-0.222	3.36	-0.143	9.83	0.240

from three-month to the one-year horizon before reducing over longer horizons. The \overline{R}^2 also increases and indeed, at the five-year horizon, the \overline{R}^2 is as high as 48.89% for the printing and publishing (Books) industry.

Regarding the defensive industries in the lower part of Table 2.4, the majority of corresponding predictive slopes are statistically insignificant, or at least less significant than slopes of cyclical sectors. The \overline{R}^2 is relatively small and does not always increase with horizons. In an extreme case, such as in agriculture sector, the \overline{R}^2 is negative.

Furthermore, in comparison of the top 30% and bottom 30% with the highest and lowest cyclicity proxy, 12 out of 15 cyclical industries exhibits statistically significant GP coefficients whereas only two defensive industries demonstrate the same pattern at the three-month horizon. These numbers increase to 13 and five at the five-year horizon, respectively. Overall, in line with the short-term horizon, Table 2.4 shows that GP tracks cyclical industry excess returns better than defensive industry excess returns over intermediate horizons.

2.3.4 Robustness tests

To test the sensitivity of our findings, we perform several robustness checks, such as subsample analysis, alternative econometric method, and alternative classification of industry cyclicity.

Subsample analysis

To investigate whether our findings are influenced by the mixed results in GP stationarity tests, we estimate the predictive regression over subsample periods. The Augmented Dickey Fuller test detects a structural break in February 2011; thus, we analyze two subsamples that are from January 1975 to February 2011 and March 2011 to December 2019. Then, we run the industry excess return predictive regression by GP in two subsamples. Because GP appears to be trend stationary in the second subsample, we control for the time trend in this period.

Table 2.5: Market correlation and industry return forecasts by GP in subsamples

The table presents the coefficients obtained from the regression of t-statistics corresponding to GP predictive slopes on the industry correlation with the market return in two subsamples. The t-statistics are Newey and West (1987) corrected t-statistics. ***, **, and * indicate positive coefficients at the one-sided 1%, 5%, and 10% significance level, respectively.

Panel A: Jan 1975 - Feb 2011				
	1-month	3-month	1-year	5-year
	Coef.	Coef.	Coef.	Coef.
Null Hypothesis (N=49)	[t-stat]	[t-stat]	[t-stat]	[t-stat]
No link between market correlation (X) and t-stat corresp. to GP slopes (Y)	5.45*** [5.85]	5.83*** [7.14]	7.69*** [7.04]	12.2*** [5.39]
Panel B: March 2011 - Dec 2019				
No link between market correlation (X) and t-stat corresp. to GP slopes (Y)	0.87** [2.05]	0.81** [1.72]	5.01*** [3.31]	8.89*** [6.36]

Table 2.5 presents the coefficients obtained from the regression of t-statistics corresponding to GP predictive slopes on the industry correlation with the market return in two subsamples. The results in both panels indicate a statistically positive relation between two variables. This finding further indicates that GP is useful in predicting cyclical

industry excess return whereas less useful for defensive industries.

Weighted least squares estimator

To assess time-series return predictability, Johnson (2019) proposes a weighted least squares estimator using ex ante variance (WLS-EV). According to Johnson (2019), WLS-EV is approximately 25% more efficient than OLS because it incorporates time-varying volatility into its estimates. Johnson (2019) further finds that under this estimator setting, numerous predictors lose their predictive power. Against this backdrop, we conduct a robustness check to investigate the predictive ability of GP and other predictors using WLS-EV.

Assume that we run the subsequent linear regression to predict returns.

$$r_{t+1} = X_t\beta + \epsilon_{t+1},$$

where r_{t+1} is the log excess return and X_t is the vector of a predictor with an optional constant. Following Johnson (2019), we use two-step WLS-EV to estimate β as

1. Estimate σ_t^2 , the conditional variance of next-month unexpected returns ϵ_{t+1} , as the fitted value in a regression of RV_{t+1} on a constant, RV_t , and $RV_{t-11,t}$. Note that RV_t is the realized variance, computed as the sum of squared daily log returns in month t , whereas $RV_{t-11,t}$ is the average realized variance in months $t-11$ through t , $RV_{t-11,t} = \frac{1}{12} \sum_{i=0}^{11} RV_{t-i}$.
2. Estimate $\hat{\beta}_{WLS-EV}$ by regressing $\frac{r_{t+1}}{\hat{\sigma}_t}$ on $\frac{X_t}{\hat{\sigma}_t}$ using OLS, where $\hat{\sigma}_t$

Table 2.6: Short-term forecasts by GP and others predictors using WLS-EV

This table presents the coefficients of the one-month predictive regression by GP and other predictors, using WLS-EV. ***, **, and * indicate significant coefficients at the one-sided 1%, 5%, and 10% level, respectively.

Industry	GP	log PD	log PE	log DE	BM	Default	Term	CAY	Output
Market	0.146***	-0.034	-0.038	-0.011	0.016	0.026	0.008	0.339	-0.675**
Aero	0.205**	-0.089	-0.135*	-0.105	0.147	-0.005	0.014	-1.021	-0.413
Agric	-0.014	-0.042	-0.079	-0.119	0.042	0.030	-0.001	0.929	-0.047
Autos	0.220**	-0.064	-0.023	0.155	0.063	0.151**	0.021	0.322	-1.357***
Banks	0.176**	0.006	0.017	0.039	-0.058	-0.037	0.038*	1.261	-0.916**
Beer	0.135**	-0.075	-0.058	0.037	0.044	0.062	-0.007	1.777**	-1.159***
BldMt	0.046	-0.046	-0.041	0.024	0.037	0.069	0.041*	1.007	-0.797*
Books	0.181**	-0.125**	-0.108*	0.078	0.173*	0.115*	0.044**	0.373	-0.630
Boxes	0.106	-0.074	-0.045	0.091	0.045	0.130**	0.034	1.182	-1.188***
BusSv	0.213***	-0.076	-0.091	-0.038	0.098	0.065	0.010	-0.826	-0.649*
Chems	0.056	-0.033	-0.027	0.024	-0.008	0.059	0.023	0.885	-0.937**
Chips	0.306***	0.007	0.038	0.087	-0.010	0.002	0.029	-0.981	-0.994**
Clths	0.162**	-0.109*	-0.122*	-0.028	0.163*	0.177**	0.016	-0.803	-0.821*
Cnstr	-0.022	-0.009	-0.072	-0.201	0.056	0.029	-0.022	-0.619	0.421
Coal	-0.523	0.143	0.074	-0.197	-0.178	0.017	-0.070	0.470	1.339
Drugs	0.161***	-0.033	-0.052	-0.050	-0.020	-0.026	-0.025	1.597*	-0.717**
ElcEq	0.109	-0.047	-0.050	-0.007	0.035	0.038	-0.003	1.538	-0.603
FabPr	0.062	-0.086	-0.106	-0.057	0.049	0.008	0.025	-0.812	-0.439
Fin	0.133*	0.001	-0.003	-0.015	-0.016	0.000	0.030	0.683	-0.392
Food	0.094*	-0.071*	-0.069*	-0.003	0.050	0.074*	0.025	2.060**	-1.043***
Fun	0.240**	-0.093	-0.099	0.005	0.124	0.039	0.032	-1.292	-0.747
Gold	-0.154	-0.051	-0.009	0.100	0.132	0.142	-0.015	-0.240	0.553
Guns	0.079	-0.002	-0.065	-0.147	0.052	-0.017	0.012	-1.550	-0.122
Hardw	0.131	0.054	0.050	-0.009	-0.082	0.036	-0.002	-0.330	-0.342
Hlth	0.096	-0.174**	-0.225**	-0.128	0.343**	0.063	-0.009	-2.359	0.137
Hshld	0.114**	-0.010	0.008	0.042	-0.023	0.045	0.017	1.544**	-0.874***
Insur	0.140**	-0.019	-0.033	-0.043	0.002	-0.049	0.017	-0.337	-0.413
LabEq	0.161**	-0.001	-0.021	-0.047	0.006	0.049	0.012	-1.163	-0.547
Mach	0.070	0.020	0.011	-0.031	-0.056	-0.002	0.007	0.042	-0.538
Meals	0.129**	-0.062	-0.069	-0.018	0.094	0.039	0.020	-0.810	-0.777*
MedEq	0.136**	0.005	-0.009	-0.034	-0.039	0.005	-0.023	-0.286	-0.524
Mines	-0.137	-0.017	-0.010	0.022	0.026	0.085	-0.035	-0.028	0.020
Oil	-0.177	-0.024	-0.066	-0.116	0.030	-0.030	0.001	0.363	0.237
Other	0.113*	-0.091	-0.134**	-0.111	0.128	0.067	-0.006	-0.456	-0.491
Paper	0.136**	-0.057	-0.033	0.072	0.050	0.104*	0.032*	0.489	-1.022**
PerSv	0.110	-0.116*	-0.103*	0.040	0.164*	0.087	0.037*	-0.426	-0.537
REst	-0.037	-0.029	-0.057	-0.107	0.102	0.064	0.082***	-1.929	0.029
Rtail	0.211***	-0.015	-0.004	0.030	0.007	0.123**	0.003	-0.179	-1.083**
Rubbr	0.177**	-0.080	-0.061	0.078	0.074	0.102	0.036	0.470	-1.173**
Ships	-0.009	0.046	-0.050	-0.284	0.039	-0.029	0.020	-2.899	0.381
Smoke	-0.075	-0.033	-0.070	-0.099	0.039	0.059	-0.018	0.870	-0.427
Soda	0.173**	-0.009	-0.002	0.020	-0.016	0.040	0.020	1.609*	-1.029**
Softw	0.211**	-0.104	-0.069	0.066	0.112	0.039	-0.009	-0.672	-0.729
Steel	-0.077	0.029	0.005	-0.085	-0.054	0.022	0.008	0.319	-0.106
Telcm	0.162***	-0.015	-0.024	-0.026	-0.019	0.013	0.008	0.963	-0.818***
Toys	0.186**	-0.129*	-0.090	0.097	0.157	0.165**	0.026	0.499	-1.469***
Trans	0.094	-0.068	-0.087	-0.045	0.076	0.069	0.024	-0.055	-0.740*
Txtls	0.122	-0.165**	-0.159**	0.077	0.223**	0.215***	0.058*	-0.138	-1.241**
Util	0.010	0.009	-0.018	-0.084	-0.012	0.007	0.009	0.572	-0.357
Whsl	0.129**	-0.106*	-0.117**	-0.029	0.160*	0.117*	0.030	-0.228	-0.644*

is the square root of σ_t^2 estimated in step 1. Standard errors are calculated using Newey and West (1987) procedure.

To apply the two-step WLS-EV estimator, we collect daily market, industry returns, and risk-free rates from [Kenneth R. French's data library](#). Table 2.6 presents the one-month predictive results by GP and other predictors, using WLS-EV. The sample period is from January 1975 to December 2019.

The results from Table 2.6 reveal that GP outperforms other predictors in predicting one-month excess returns, with 22 and 27 statistically positive GP coefficients at the 5% and 10% level, respectively. Meanwhile, as the second most effective predictor, output gap can predict 16 and 22 industries, correspondingly. In contrast, other predictors are not much useful in predicting one-month excess returns at the industry level.

Furthermore, by regressing t-statistics corresponding to GP predictive slopes on the industry correlation with the market, we find that the coefficient from this regression equals 5.07 (with the Newey and West (1987) corrected t-value of 3.81 and \overline{R}^2 of 27.52%). The evidence confirms the positive and statistically significant relation between two variables and that GP predicts cyclical better than defensive industries. Overall, our findings remain unchanged, regardless of the econometric model.

Alternative classification of industry cyclical

In the benchmark results, to conduct a detailed cross-industry analysis, we use the correlation between industry and market returns as a proxy for the industry cyclical. We also consider an alternative classification proposed by Boudoukh et al. (1994), which is based on the correlation between industrial and aggregate production/output growth, to test the robustness of our findings in a more aggregated industry level.

We obtain the seasonally adjusted industrial production data from the G.17 release of the Board of Governors of the Federal Reserve System from 1975 to 2019. In this analysis, we focus on 22 industries³ for which a matching series of industrial production data exists. Then, we calculate the quarterly correlation between each industry and aggregate production growth and rank the industries accordingly. Monthly VW returns of these industries are available from [Kenneth R. French's data library](#).

Panels A and B in Table 2.7 presents one-month, three-month, one-year, and five-year GP predictive slopes for six cyclical and six noncyclical industry excess returns. GP predictive slopes are positive and statistically significant for all six cyclical industries and all

³The industries are Apparel and other Textile Products, Chemicals, Electrical/Electronic Equipment, Food Products, Furniture and Fixtures, Instruments and Related Products, Lumber and Wood Products, Medical Manufacturing, Metal Products, Mining, Non-electrical, Machinery, Paper Products, Petroleum and Coal Products, Primary Metals, Printing and Publishing, Rubber and Plastics, Stone, Clay and Glass Products, Textile Mill Products, Tobacco Products, Transportation Equipment, and Utilities.

Table 2.7: Industrial output correlation and return forecasts by GP

The table presents one-month, three-month, one-year, and five-year GP predictive slopes for six cyclical and six noncyclical industry excess returns in Panels A and B. Industry classification is based on the correlation between industrial and aggregate production/output growth proposed by Boudoukh et al. (1994). Panel C presents the coefficients obtained from the regression of t-statistics corresponding to GP predictive slopes on the industry output correlation. The t-statistics are Newey and West (1987) corrected t-statistics. ***, **, and * indicate positive coefficients at the one-sided 1%, 5%, and 10% significance level, respectively. The sample period is from January 1975 to December 2019.

Panel A: Cyclical Industries				
Industry (Output correlation)	1-month slope	3-month slope	1-year slope	5-year slope
Metal Products (0.85)	0.135**	0.139**	0.122**	0.043**
Electrical/Electronic Equipment (0.80)	0.407***	0.413***	0.373***	0.210***
Furniture and Fixtures (0.77)	0.169**	0.193**	0.221***	0.110***
Rubber and Plastics (0.71)	0.183**	0.178***	0.156***	0.040**
Chemicals (0.70)	0.143***	0.135***	0.156***	0.131***
Non-electrical Machinery (0.69)	0.257**	0.274**	0.256***	0.072***
Panel B: Noncyclical Industries				
Medical Manufacturing (0.33)	0.046	0.046	0.059	0.037*
Petroleum and Coal Products (0.32)	-0.048	-0.049	-0.039	0.015
Mining (0.31)	-0.142	-0.140	-0.214	-0.206
Food Products (0.23)	0.120**	0.120***	0.137***	0.113***
Tobacco Products (0.15)	-0.123	-0.138	-0.099	-0.021
Utilities (0.10)	0.038	0.043	0.087*	0.033**
Panel C: Hypothesis tested				
Null Hypothesis (N=22)	Coef. [t-stat]	Coef. [t-stat]	Coef. [t-stat]	Coef. [t-stat]
No link between Output correlation (X) and t-stat corresp. to GP slopes (Y)	3.29*** [5.09]	3.44*** [5.04]	3.75*** [3.60]	4.65*** [2.85]

horizons. At the same time, GP predictive slopes for noncyclical industries except the food industry are statistically insignificant in most cases. The results in Panel C further confirm the positive relation between t-statistics corresponding to GP predictive slopes and production growth correlation for 22 industries/observations at the 1% significance level. Consistent with the benchmark findings, the results in this section demonstrate that GP tracks cyclical better than defensive industries over short and intermediate horizons.

2.4 Out-of-sample predictability

The previous sections so far address in-sample predictability extensively. Focusing more on in-sample predictability is reasonable because according to Inoue and Kilian (2005), in-sample results in most cases are more credible than out-of-sample results. Nevertheless, one often wants to know how a predictor performs out-of-sample and a satisfactory out-of-sample performance would add more statistical power to in-sample performance. In this section, we use three proxies to assess GP forecast ability at the one-month horizon in an out-of-sample context. The first measure is the unconstrained out-of-sample R^2 :

$$R_{OS}^2 = 1 - \frac{\sum_{t=T_1+1}^T (r_t^e - \hat{r}_t^e)^2}{\sum_{t=T_1+1}^T (r_t^e - \bar{r}_t^e)^2},$$

where T is the whole sample length, T_1 is the initial training window size, r_t^e is the actual excess return at time t , \hat{r}_t^e is the excess return estimated by Formula (2.1) using observations from time 1 to $t - 1$, and \bar{r}_t^e is the average excess return from time 1 to $t - 1$. Motivated by the work of Campbell and Thompson (2008), we also compute the constrained out-of-sample R^2 , restricting the sign of the estimated excess returns to positive numbers only. In general, a positive R_{OS}^2 implies that the GP-based estimate outperforms the historical average benchmark, which further indicates GP possesses out-of-sample forecast power.

To obtain the corresponding p-value, we formally test the null hy-

pothesis of $R_{OS}^2 \leq 0$ by regressing the subsequent Clark and West (2007) adjusted-MSPE statistic on a constant.

$$f_{t+1} = (r_{t+1}^e - \bar{r}_{t+1}^e)^2 - (r_{t+1}^e - \hat{r}_{t+1}^e)^2 + (\bar{r}_{t+1}^e - \hat{r}_{t+1}^e)^2$$

Finally, we calculate the following out-of-sample F-statistic and use critical values derived by McCracken (2007) for statistical inference. Similarly, the null hypothesis is $R_{OS}^2 \leq 0$.

$$OS_F = (T - T_1) \left[\frac{\sum_{t=T_1+1}^T (r_t^e - \bar{r}_t^e)^2}{\sum_{t=T_1+1}^T (r_t^e - \hat{r}_t^e)^2} - 1 \right]$$

Noticeably, we apply a recursive window to forecast out-of-sample excess returns. Compared to a rolling window, the approach using the recursive one is favored because it creates more stable parameters, which is particularly useful when handling long time series with potential structural changes. Furthermore, we do not use the conditional method but the standard OLS to estimate out-of-sample excess returns because the conditional method requires the information on GP_t , which is not available at time $t - 1$. Following Huang and Kilic (2019), we choose 120 and 180 months as the sizes of the initial training window.

Table 2.8 presents out-of-sample forecast results by GP for excess market and 49 industry returns at the one-month horizon. R_{IS}^2 is the in-sample R^2 . Panels A and B present the unconstrained and constrained out-of-sample R_{OS}^2 using 120- and 180-month recursive windows. The p-values are associated with the adjusted-MSPE statistic of

Table 2.8: Out-of-sample forecasts by GP

The table shows out-of-sample GP forecast for the one-month excess market and industry returns.

Industry	$R_{IS}^2(\%)$	Panel A: Unconstrained $R_{OS}^2(\%)$				Panel B: Constrained $R_{OS}^2(\%)$			
		120m	p-val	180m	p-val	120m	p-val	180m	p-val
Market	1.02	0.70***	0.03	0.85***	0.03	1.09***	0.01	1.33***	0.01
BusSv	1.17	1.10***	0.01	1.14***	0.02	1.57***	0.00	1.74***	0.01
Fin	0.57	-0.09	0.12	-0.24	0.14	0.66***	0.05	0.59**	0.07
ElcEq	0.41	-0.32	0.10	-0.34	0.10	0.17*	0.10	0.12	0.11
Mach	0.03	-0.43	0.20	-0.43	0.20	0.10	0.15	0.19	0.14
Whlsl	0.47	-0.29	0.07	-1.17	0.12	1.16***	0.02	0.65**	0.05
BldMt	0.26	-0.06	0.09	-0.09	0.09	0.56***	0.05	0.66**	0.05
LabEq	0.74	-0.05	0.10	-0.07	0.10	0.87***	0.02	1.01***	0.03
Chemts	-0.01	-0.57	0.16	-0.65	0.16	0.25*	0.10	0.26*	0.11
Chips	1.75	0.96***	0.03	1.03***	0.04	1.17***	0.01	1.23***	0.01
Books	1.00	0.41**	0.02	0.33*	0.03	0.32**	0.04	0.20	0.05
Rtail	0.91	-0.23	0.05	-0.37	0.05	0.82***	0.03	0.78***	0.04
Trans	0.06	-0.59	0.14	-0.80	0.15	0.49**	0.07	0.47**	0.09
Rubbr	0.48	-0.15	0.07	-0.41	0.09	0.79***	0.03	0.68**	0.05
Paper	0.23	-0.58	0.13	-0.80	0.14	0.47***	0.06	0.52**	0.07
Cnstr	-0.16	-0.53	0.13	-0.56	0.15	-0.46	0.15	-0.47	0.17
Steel	-0.11	-0.76	0.18	-0.78	0.19	-0.14	0.19	-0.16	0.19
Other	0.23	-0.10	0.14	0.01	0.13	0.15	0.10	0.32*	0.06
Banks	0.73	0.42	0.05	0.19	0.08	1.26***	0.01	1.07***	0.02
Fun	0.41	0.01	0.11	-0.12	0.13	0.48**	0.06	0.43**	0.08
Insur	0.51	0.24*	0.11	0.30*	0.11	0.62***	0.04	0.75**	0.04
Hardw	0.92	-0.15	0.09	-0.32	0.10	0.07	0.10	0.03	0.11
Telem	1.71	0.99***	0.02	1.45***	0.02	1.03***	0.01	1.47***	0.01
MedEq	0.23	-0.05	0.14	-0.11	0.15	0.30**	0.09	0.10	0.13
Aero	0.48	-0.19	0.08	-0.90	0.13	1.26***	0.02	0.85***	0.05
Softw	0.83	0.44**	0.04	0.85***	0.03	0.93***	0.02	1.43***	0.01
Meals	0.41	-0.85	0.08	-1.09	0.09	1.04***	0.02	1.06***	0.03
Autos	0.88	0.11	0.05	0.02	0.06	0.50**	0.04	0.44**	0.06
Clths	0.27	-0.49	0.11	-1.18	0.16	1.24***	0.01	0.88***	0.04
Boxes	0.08	-0.88	0.17	-0.80	0.16	0.36**	0.09	0.63**	0.06
PerSv	-0.02	-0.55	0.14	-1.28	0.18	0.81***	0.03	0.45**	0.09
Hshld	0.39	-0.83	0.11	-0.67	0.10	0.70***	0.04	0.81***	0.05
Toys	0.30	-0.23	0.10	-0.14	0.09	0.77***	0.04	1.02***	0.03
REst	0.00	-0.12	0.13	-0.13	0.13	0.27*	0.08	0.30*	0.08
Drugs	0.41	-0.03	0.10	0.13	0.08	0.30**	0.07	0.46**	0.06
Txtls	-0.03	-0.59	0.12	-0.76	0.14	0.40**	0.06	0.37*	0.08
Ships	-0.19	-0.59	0.14	-0.79	0.11	-0.08	0.20	-0.14	0.19
FabPr	-0.04	-0.43	0.20	-0.42	0.20	0.14	0.15	0.21*	0.13
Mines	-0.12	-0.52	0.17	-0.54	0.17	-0.28	0.20	-0.27	0.20
Oil	0.05	-0.70	0.20	-0.65	0.20	-0.65	0.20	-0.60	0.20
Food	0.05	-0.94	0.18	-1.44	0.19	0.07	0.11	-0.12	0.13
Hlth	-0.07	-0.57	0.19	-0.73	0.18	-0.19	0.20	-0.25	0.20
Beer	0.49	-0.07	0.06	0.07	0.06	0.43**	0.05	0.70**	0.04
Agric	-0.19	-0.53	0.20	-0.73	0.19	-0.14	0.20	-0.25	0.19
Soda	0.33	-0.51	0.13	-1.00	0.17	0.68***	0.04	0.31*	0.10
Guns	-0.10	-0.62	0.20	-0.90	0.19	0.25*	0.14	0.16	0.17
Util	-0.12	-0.89	0.11	-1.08	0.08	-0.71	0.14	-0.87	0.10
Coal	0.88	0.46**	0.09	0.50**	0.09	0.32**	0.12	0.30*	0.13
Smoke	0.05	-0.58	0.20	-0.65	0.20	-0.57	0.20	-0.64	0.20
Gold	-0.19	-0.58	0.10	-0.61	0.11	-0.06	0.20	-0.02	0.19

Clark and West (2007). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level based on the critical value derived by McCracken (2007), respectively. Finally, the null hypothesis in both cases is $R_{OS}^2 \leq 0$.

Panel A shows limited evidence that GP exhibits out-of-sample forecast power for the excess industry returns at the one-month horizon. Only at the market level and in very few sectors, the unconstrained out-of-sample R^2 is positive and statistically significant. In addition, with either 120- or 180-month window, the majority of the unconstrained R_{OS}^2 is negative. The values of the adjusted-MSPE and F statistics further reveal that forecasting errors using GP are significantly higher than those using the historical mean in most industries.

However, limited evidence supporting the unconstrained GP out-of-sample predictive power does not necessarily mean that GP cannot predict out-of-sample excess returns at all. According to Campbell and Thompson (2008) and Cochrane (2008), the unconstrained out-of-sample forecast potentially suffers from bias. Estimating a regression over a subsample can easily produce adverse outcomes, such as negative excess returns, leading to a downward bias in out-of-sample performance. Meanwhile, in practice, an investor would rule out a regression that predicts negative excess returns. Accordingly, we compute the constrained out-of-sample R^2 by restricting the sign of the estimated excess returns to positive only whereas setting negative estimated excess returns to zeros.

Panel B shows that at the market level, GP generates a positive

constrained R_{OS}^2 of 1.09% and 1.33% corresponding to 120- and 180-month estimation windows. These numbers are statistically significant at the 5% level or better and roughly in line with the in-sample R^2 of 1.02%. A similar pattern holds in at least 30 out of 49 industries, implying GP exhibits strong constrained out-of-sample predictability across sectors. Notably, significant constrained out-of-sample R^2 mainly exists in cyclical sectors, which exhibit significant in-sample coefficients, including business services (BusSv), trading (Fin), and wholesale.

In summary, this section presents weak evidence for the unconstrained GP out-of-sample predictive power across industries at the one-month horizon. However, once we impose an economic restriction on the sign of the estimated excess returns, GP is useful in predicting market and many industry excess returns out-of-sample.

2.5 Economic significance of GP forecasts

In this section, we demonstrate the economic significance of GP forecasts by constructing a GP-based out-of-sample trading strategy. Consistent with the previous section, we focus on the one-month horizon and apply either the 120- or the 180-month recursive training window. The out-of-sample period starts from 1985:02 or 1990:02, respectively.

The construction of the GP-based strategy is as follows. At each month t , we conduct the one-month return regression on GP using the recursive window to estimate parameters for the market and each in-

dustry. Then, we form expected return \hat{r}_{t+1} based on these parameters and the latest GP observation. As in many related studies, we calculate the Markowitz optimal weight on risky assets (market or industry portfolios) as follows:

$$w_t = \frac{\hat{r}_{t+1} - rf_{t+1}}{\gamma \hat{\sigma}_t^2},$$

where rf_{t+1} is the risk-free rate from t to $t + 1$ (known at time t), γ is the relative risk aversion that typically receives the value of three, and $\hat{\sigma}_t^2$ is the variance of the stock returns estimated using all available data up to time t . Accordingly, the weight on the risk-free rate is $(1 - w_t)$. Following Campbell and Thompson (2008), to prevent excessive leverage or large short sales, we impose a constraint on the portfolio weight $w_t \in [-0.5; 1.5]$.

To evaluate performance of the GP-based strategy, we employ the passive buy-and-hold strategy as the benchmark strategy. First, we compare Sharpe ratios of two strategies. Then, motivated by Campbell and Thompson (2008) and Rapach, Strauss, and Zhou (2010) among others, we measure the certainty equivalent return (CE) as the difference between the utility derived from the GP-based and buy-and-hold approach:

$$CE = \bar{r}_{GP} - \bar{r}_I + \frac{\gamma}{2}(\sigma_I^2 - \sigma_{GP}^2)$$

where \bar{r}_{GP} or \bar{r}_I and σ_{GP}^2 or σ_I^2 are mean and variance of the GP-based or buy-and-hold strategy over the out-of-sample period. Intuitively,

Table 2.9: Economic significance of GP forecasts

The table presents the annualized performance of the GP-based and buy-and-hold strategy. The out-of-sample period starts from 1985:02 or 1990:02.

Industry	Panel A: 120-month window			Panel B: 180-month window		
	Buy-hold SR	GP-based SR	CE (%)	Buy-hold SR	GP-based SR	CE (%)
Market	0.561	0.719	2.92	0.570	0.759	3.43
BusSv	0.480	0.694	3.75	0.521	0.768	4.17
Fin	0.477	0.557	1.75	0.500	0.587	2.05
ElcEq	0.508	0.527	0.54	0.535	0.558	0.49
Mach	0.436	0.393	0.18	0.435	0.410	0.50
Whlsl	0.429	0.534	1.77	0.465	0.526	1.00
BldMt	0.451	0.491	0.81	0.437	0.490	0.96
LabEq	0.423	0.565	3.37	0.508	0.655	2.71
Chems	0.485	0.461	-0.36	0.452	0.447	-0.13
Chips	0.427	0.730	7.95	0.482	0.820	8.70
Books	0.289	0.493	3.62	0.263	0.492	4.03
Rtail	0.585	0.746	2.65	0.599	0.746	2.50
Trans	0.462	0.491	0.56	0.484	0.511	0.45
Rubbr	0.479	0.587	2.18	0.491	0.589	1.93
Paper	0.441	0.513	1.34	0.416	0.491	1.29
Cnstr	0.357	0.295	0.59	0.366	0.315	0.58
Steel	0.199	0.026	4.35	0.202	0.037	4.51
Other	0.199	0.208	1.77	0.098	0.108	2.61
Banks	0.455	0.570	2.41	0.474	0.566	1.92
Fun	0.515	0.544	1.08	0.474	0.503	1.01
Insur	0.537	0.563	0.41	0.553	0.608	1.06
Hardw	0.328	0.419	4.60	0.408	0.456	3.34
Telem	0.463	0.783	6.03	0.380	0.789	7.47
MedEq	0.672	0.587	-1.46	0.683	0.596	-1.32
Aero	0.514	0.648	2.66	0.590	0.707	2.15
Softw	0.531	0.752	3.83	0.577	0.834	3.82
Meals	0.608	0.773	2.27	0.639	0.804	2.46
Autos	0.265	0.483	6.61	0.256	0.465	6.48
Clths	0.488	0.596	2.41	0.500	0.578	1.72
Boxes	0.480	0.539	1.28	0.435	0.529	1.96
PerSv	0.262	0.318	1.70	0.313	0.338	1.01
Hshld	0.572	0.628	0.70	0.602	0.678	1.24
Toys	0.304	0.392	3.39	0.294	0.420	3.69
REst	0.109	0.139	5.86	0.162	0.224	6.41
Drugs	0.673	0.655	-0.07	0.629	0.642	0.56
Txtls	0.308	0.372	3.04	0.235	0.279	3.23
Ships	0.320	0.242	2.18	0.483	0.373	-0.21
FabPr	0.209	0.155	3.18	0.216	0.171	3.59
Mines	0.356	0.224	0.73	0.365	0.228	0.57
Oil	0.410	0.370	-1.85	0.379	0.350	-1.71
Food	0.665	0.647	0.16	0.580	0.565	0.13
Hlth	0.307	0.239	-0.55	0.368	0.322	-0.23
Beer	0.715	0.776	1.36	0.638	0.721	1.82
Agric	0.380	0.283	-0.95	0.403	0.298	-1.25
Soda	0.496	0.649	3.41	0.489	0.584	2.43
Guns	0.538	0.537	0.09	0.622	0.617	-0.15
Util	0.589	0.509	-0.94	0.562	0.496	-0.79
Coal	0.163	0.269	14.08	0.169	0.296	15.85
Smoke	0.580	0.538	-2.95	0.507	0.450	-3.43
Gold	0.157	0.013	14.18	0.112	-0.043	15.95

the CE measures utility gains for a mean-variance investor that pursues the GP-based instead of buy-and-hold strategy. The CE further implies the fee a mean-variance investor is willing to pay to invest in the GP-based instead of passive strategy.

Table 2.9 presents the Sharpe ratios (SR) and the annualized certainty equivalent return (CE) derived from the GP-based and buy-and-hold strategy. The out-of-sample period starts from 1985:02 or 1990:02, corresponding to the 120- or the 180-month training window. Table 2.9 demonstrates that, for the market portfolio, the GP-based approach produces SR of 0.719 and 0.759, which are marginally higher than SR of the passive strategy (0.561 and 0.570). The results from industry portfolios further reinforce the superiority of the GP-based over buy-and-hold strategy. In particular, the GP-based strategy delivers higher SR than the passive approach for at least 32 out of 49 industries. Among these industries, the GP-based strategy dominates farthestmost in communication (telcm), business services (bussv), and electronic equipment (chips).

The outperformance of the GP-based strategy becomes more pronounced in terms of CE. At the market level, the annualized CE are 2.92% and 3.43%, using the 120- and 180-month training window, respectively. Across all industries, the annualized CE is positive in 41 out of 49 industries with the average of roughly 2.4%. Those numbers imply the extra utility gains a mean-variance investor with a risk aversion of three would obtain following the GP-based instead of passive strategy. Noticeably, the outperformance of the GP-based strategy is

even stronger given a higher level of relative risk aversion.

Interestingly, in a few sectors namely non-metallic and industrial metal mining (mines), food products (food), and precious metals (gold), the GP-based approach generates a lower Sharpe ratio but a higher utility relative to the passive strategy. One explanation is that in those sectors, the buy-and-hold strategy delivers a high return but an extremely high variance. As a mean-variance investor with a risk aversion of three weigh strongly with the low-variance portfolio, he or she would still prefer the GP-based to the passive strategy.

Overall, this section suggests that GP is highly useful in constructing a profitable trading strategy and that the GP-based strategy outperforms the buy-and-hold strategy in the stock market and many sectors. Economically, at the one-month horizon, a mean-variance investor is willing to pay an annual fee of approximately 2.4% in exchange for the GP-based strategy across all industries.

2.6 Conclusion

This chapter documents new evidence of GP forecasting ability over the US industry excess returns in-sample and out-of-sample. Using monthly data from 1975 to 2019, we find that GP predicts cyclical better than defensive industry excess returns over short and intermediate horizons. This finding is robust to several robustness checks and economically justifiable. On the one hand, GP exhibits power to capture cyclical components of stock returns. On the other hand, cyclical

industry returns highly correlate with business cycles while defensive industry returns do not, leading to the fact that GP can track cyclical industry stock returns better.

The one-month out-of-sample forecast by GP is weak, but this result probably suffers from downward bias according to Campbell and Thompson (2008) and Cochrane (2008). Once we impose an economic restriction on the sign of the estimated excess return, GP is useful in predicting market and many industry excess returns out-of-sample.

Finally, the chapter outlines a GP-based trading strategy that outperforms the buy-and-hold strategy in various sectors at the one-month horizon. On average, the GP-based strategy generates an annualized certainty equivalent return of approximately 2.4% higher than the buy-and-hold strategy out-of-sample across all sectors. This finding is appealing to many stakeholders, who are particularly interested in forming a sectoral trading strategy using a high-frequency and model-free predictor.

3

Volatility Spillovers between Commodity Markets and Equity Sectors: The Case of Commodity Indices¹

3.1 Introduction

The linkage between equity and commodity markets has been an important avenue for research over the past decades. The asset pricing theory indicates that variations in commodity prices might cause un-

¹This chapter is based on Pham, Quynh T, 2021b, Volatility spillovers between commodity markets and equity sectors: The case of commodity indices, *Unpublished Working Paper* .

certainty in the equity market via at least two channels. First, given that commodities are major inputs/outputs in the production process, an increase in commodity prices could induce higher costs/revenues for companies, which in turn; decreases/increases firm expected cash-flows. Second, commodity price shocks likely shift future discount rates by changing consumer prices, inflationary expectations, and/or economic conditions. Both effects lead to the fluctuations in stock prices.

In addition, a growing body of evidence shows that different equity sectors tend to react asymmetrically to changes in commodity prices. Broadly, sector sensitivities to commodity price shocks depend on whether the shocks are direct or indirect to the industry and whether the sector exhibits the capacity to transfer commodity shocks to its consumers. As an example, sectors related to oil and transportation are more dependent on energy commodities than health care and banking sectors. Meantime, the agriculture sector is more likely affected by price shocks from grains and oilseeds, livestock, and soft commodities.

Although the literature examining the mean and volatility spillovers across two markets in the United States is vast, most of the existing research particularly focuses on the transmission mechanism between crude oil and equity at the market and sectoral level. These studies confirm the existence of a bidirectional volatility spillover between oil and S&P500 index and a heterogeneous intensity of transmission across stock sectors (Hammoudeh, Dibooglu, and Aleisa (2004);

Malik and Ewing (2009); Elyasiani, Mansur, and Odusami (2011); Salisu and Oloko (2015); and Khalfaoui, Boutahar, and Boubaker (2015)). Based on these findings on volatility spillovers, numerous articles demonstrate a major role of crude oil in cross-market hedging for equity (Sadorsky (2012); Ahmad (2017); Ahmad, Sadorsky, and Sharma (2018); Olson, Vivian, and Wohar (2019); and Laing, Lucey, and Lutkemeyer (2020)). In the context of portfolio allocation, Arouri, Jouini, and Nguyen (2011); Chkili, Aloui, and Nguyen (2014); and Pham (2019) further find that investors in the US market should hold more stocks than crude oil to hedge their portfolio pairs. More details on the relation between oil and equity can be found in the survey by Smyth and Narayan (2018).

In this chapter, instead of using a single commodity, to investigate volatility spillovers between commodities and major US equity sectors, we use several commodity indices as proxies, within the framework of a bivariate BEKK-GARCH model. Then, we construct the hedge ratios and optimal weights for stock sectors in the pair with commodity indices. Finally, we demonstrate the economic implications for investors by comparing the effectiveness of the diversification strategies using commodity indices and crude oil.

At least two reasons exist for this particular study. First, most of the previous work draws attention to the interdependence of oil and equity. Despite of the importance of crude oil in the global market, changes in oil prices do not necessarily reflect total variations in the commodity market. Meanwhile, because various commodities with

different weights constitute indices, changes in these indices are more likely to capture the total risk exposure in the commodity market. Thus, using indices to investigate transmission and build the diversification strategies across two markets can eliminate potential bias. Second, over the past years, a few studies reveal an increasing trend of index investment in the commodity market, referred to as the financialization of commodities (Tang and Xiong (2012); Cheng and Xiong (2014); Hamilton and Wu (2015); Adams and Glueck (2015); Basak and Pavlova (2016); and Brogaard, Ringgenberg, and Sovich (2019)). Given this phenomenon, results from this study become even more important to investors in making their optimal investment and hedging decisions.

To preview our findings, first, we find a significant volatility spillover between commodity indices and US equity segments and the transmission is stronger from commodities to stocks than from stocks to commodities. Second, the volatility spillovers from commodities vary across sectors. These findings further imply a considerable cross-sector variation in the hedging costs and optimal weights for the portfolio pair of commodities and equity. In the context of portfolio allocation, this chapter suggests that investors in the US market should hold fewer stocks than commodity indices to minimize the risk exposure. Finally, by examining the risk-adjusted returns and hedging effectiveness, we find that the strategies involving commodity indices often lead to additional diversification benefits relative to those using WTI crude oil. As a recommendation, investors should use commodity in-

dices instead of WTI crude oil to hedge and diversify the risks of their sectoral investments.

The structure of this chapter is organized as follows. Section 3.2 demonstrates the methodology. Section 3.3 and 3.4 present data and empirical results, respectively. Finally, section 3.5 concludes our findings.

3.2 Methodology

To examine the volatility transmission between commodity indices and US equity sectors, we apply the unrestricted BEKK-GARCH model of Engle and Kroner (1995). One advantage of this model is that it eliminates the generated regressor problem associated with the two-step estimation (Malik and Ewing (2009)). In addition, unlike the other diagonal bivariate GARCH models, the BEKK-GARCH model does not impose restrictions on the correlation between two series over time. Thus, after we control the convergence problems, this model is more superior because it simultaneously captures the interaction in mean and conditional variance of all variables.

Next, following the previous literature, we define the mean equation for each pair of the commodity index and stock sector return as follows:

$$R_t = \mu + \Phi R_{t-1} + \varepsilon_t \quad (3.1)$$

$$\varepsilon_t = H_t^{1/2} \eta_t \quad (3.2)$$

where:

- $R_t = (r_t^S, r_t^C)'$ is the vector of returns on the equity sector and the commodity index.
- μ is the vector of long-term drifts.
- Φ is a 2x2 diagonal coefficient matrix.
- $\varepsilon_t = (\varepsilon_t^S, \varepsilon_t^C)'$ is the vector of residuals in the mean equations for stock sector and commodity index returns, respectively.
- $\eta_t = (\eta_t^S, \eta_t^C)'$ is the vector of i.i.d. random errors.
- $H_t = \begin{pmatrix} h_t^S & h_t^{SC} \\ h_t^{SC} & h_t^C \end{pmatrix}$ is the positive semi-definite matrix of conditional covariance of the error term that satisfies the following quadratic BEKK parameterization.

$$H_{t+1} = C'C + B'H_tB + A'\varepsilon_t\varepsilon_t'A \quad (3.3)$$

where $C = \begin{pmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{pmatrix}$, $A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$ and $B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}$ are matrices of parameters indicating the extent to which current levels of conditional covariance are related to recent squared errors and previous covariance lags, respectively. Additionally, expanding Equation (3.3) in the bivariate GARCH (1,1) model gives the subsequent equations, which reveal the existence of any shocks and volatility trans-

mission across two series over time.

$$\begin{aligned}
h_{t+1}^S &= c_{11}^2 + b_{11}^2 h_t^S + b_{21}^2 h_t^C + a_{11}^2 (\varepsilon_t^S)^2 + a_{21}^2 (\varepsilon_t^C)^2 + 2b_{11}b_{21}h_t^{SC} \\
&\quad + 2a_{11}a_{21}\varepsilon_t^S\varepsilon_t^C \\
h_{t+1}^C &= c_{21}^2 + c_{22}^2 + b_{12}^2 h_t^S + b_{22}^2 h_t^C + a_{12}^2 (\varepsilon_t^S)^2 + a_{22}^2 (\varepsilon_t^C)^2 + 2b_{12}b_{22}h_t^{SC} \\
&\quad + 2a_{12}a_{22}\varepsilon_t^S\varepsilon_t^C \\
h_{t+1}^{SC} &= c_{11}c_{21} + b_{11}b_{12}h_t^S + b_{21}b_{22}h_t^C + a_{11}a_{12}(\varepsilon_t^S)^2 + a_{21}a_{22}(\varepsilon_t^C)^2 \\
&\quad + (b_{11}b_{22} + b_{12}b_{21})h_t^{SC} + (a_{11}a_{22} + a_{12}a_{21})\varepsilon_t^S\varepsilon_t^C
\end{aligned}$$

Finally, we estimate the parameters by maximizing the following likelihood function, assuming normally distributed random errors.

$$L(\theta) = -T \ln(2\pi) - \frac{1}{2} \sum_{t=1}^T (\ln |H_t| + \varepsilon_t' H_t^{-1} \varepsilon_t)$$

where T is the number of observations and θ is the vector of unknown parameters.

3.3 Data

3.3.1 Commodity Indices

In this study, we use five different commodity indices as proxies for the commodity market, which are the Bloomberg Commodity Index (BCOM), Thomson Reuters/CoreCommodity Index (CRB), Dow Jones Commodity Index (DJCI), Rogers International Commodity Index (RICI), and SummerHaven Dynamic Commodity Index (SDCI). These indices are among the most widely recognized benchmarks that

Table 3.1: Information on commodity indices

The table summarizes some information on the Bloomberg Commodity Index (BCOM), Thomson Reuters/CoreCommodity Index (CRB), Dow Jones Commodity Index (DJCI), Rogers International Commodity Index (RICI), and SummerHaven Dynamic Commodity Index (SDCI).

Sticker	Data Source	Inception Date	Description
BCOM	EIKON	Jan 2, 1991	<ul style="list-style-type: none"> • Index comprises 23 commodities futures, representing 21 commodities that are grouped in five segments: Energy, Agriculture, Industrial Metals, Precious Metals, and Livestocks. • Commodity weightings are based on production (33%) and liquidity (67%). • Weighting range of one single commodity in the index is [2%, 15%]. • Index is rebalanced annually.
CRB	EIKON	Jan 3, 1994	<ul style="list-style-type: none"> • Index comprises 19 commodities futures that are grouped in four segments: Energy, Metals, Agriculture, and Livestocks. • Petroleum products are capped at 33% and others are weighted by liquidity. • Index is rebalanced monthly.
DJCI	EIKON	Jan 8, 1999	<ul style="list-style-type: none"> • Index comprises 28 commodities futures, representing 20 commodities that are liquidity-weighted in three segments: Energy, Metals, and Agriculture & Livestocks. • Segments are equally weighted. • Weighting range of one single commodity in the index is [0.25%, 17%]. • Index is rebalanced quarterly.
RDCI	Beeland Interests, Inc.	Jul 31, 1998	<ul style="list-style-type: none"> • Index comprises 38 commodities futures quoted in four currencies. • Commodities are weighted by consumption. • Index is rebalanced annually.
SDCI	SummerHaven Index Management	Jan 2, 1991	<ul style="list-style-type: none"> • Index comprises futures contracts of 7 commodities with greatest backwardation and 7 ones with greatest 12-month price increase. • Commodities are equally weighted. • Index is rebalanced monthly.

represent the global commodity market. Table 3.1 summarizes some information on these commodity indices.

Following a few previous studies, we use weekly data in this analysis. The use of weekly data is preferable because it significantly reduces potential bias that arises from using daily data, such as the bid-ask effect and non-synchronous trading days. In addition, using weekly data tends to be more efficient than lower frequency data in capturing the dynamic interdependence across commodity and equity markets.

Moreover, we choose the sample period from January 1, 1991 to December 31, 2019 to cover the earliest available data of commodity indices. For each data series, weekly returns are calculated as $100 * \ln(P_t/P_{t-1})$, where P_t is the Wednesday closing commodity index at week t . If the commodity market closes on Wednesday, we use the value of the previous trading day for calculation.

Finally, to compare the effectiveness of the diversification strategies using commodity indices and crude oil in the latter section, we collect the West Texas Intermediate (WTI) oil price from the [US Energy Information Administration database](#). WTI crude oil is produced in Texas and Southern Oklahoma, serving as the primary benchmark for the US oil market.

3.3.2 US equity sectors

For the equity market, our sample data cover 11 major sectors in the US, which are Consumer Nondurables (NonDur); Consumer Durables (Durbl); Manufacturing (Manuf); Oil, Gas, and Coal Extraction and Products (Engry); Chemicals and Allied Products (Chems); Business

Table 3.2: Descriptive statistics of return series

The table presents the descriptive statistics of weekly return series for the commodity indices, the WTI oil price, and US equity sectors. The commodity indices are the Bloomberg Commodity Index (BCOM), Thomson Reuters/CoreCommodity Index (CRB), Dow Jones Commodity Index (DJCI), Rogers International Commodity Index (RICI), and Summer-Haven Dynamic Commodity Index (SDCI). Jarque–Bera refers to a statistical test for normality based on skewness and excess kurtosis. ARCH refers to the LM-statistics of the Wald test for conditional heteroscedasticity in the residuals. ***, **, and * indicate that the null hypotheses are rejected at the 1%, 5%, and 10% significance level, respectively. The longest sample period is from January 1, 1991 to December 31, 2019.

Index	Mean (%)	Std. dev. (%)	Skew.	Kurt.	Observation	Jarque-Bera	ARCH
BCOM	0.04	1.98	-0.39	2.53	1513	436.06***	54.74***
CRB	0.08	2.17	-0.32	1.61	1356	167.80***	57.75***
DJCI	0.10	2.16	-0.45	2.26	1093	266.43***	70.64***
RICI	0.08	2.45	-0.36	1.87	1117	184.87***	60.66***
SDCI	0.17	1.82	-0.63	3.33	1513	790.95***	125.84***
WTI oil	0.06	4.83	-0.15	3.01	1513	572.77***	80.30***
Sector	Mean (%)	Std. dev. (%)	Skew.	Kurt.	Observation	Jarque-Bera	ARCH
NoDur	0.20	1.83	-0.73	3.77	1513	1022.25***	83.44***
Durbl	0.15	3.29	-0.66	4.79	1513	1540.86***	73.77***
Manuf	0.22	2.61	-0.80	4.45	1513	1401.74***	113.32***
Enrgy	0.16	2.96	-0.61	3.18	1513	723.11***	156.74***
Chems	0.20	2.10	-0.73	4.85	1513	1607.50***	78.65***
BusEq	0.23	3.31	-0.58	3.19	1513	720.02***	58.53***
Telcm	0.15	2.56	-0.52	5.49	1513	1950.59***	91.05***
Utils	0.18	2.10	-0.88	7.27	1513	3502.28***	69.34***
Shops	0.22	2.37	-0.40	3.06	1513	623.59***	70.67***
Hlth	0.21	2.31	-0.36	2.31	1513	364.88***	39.16***
Money	0.21	3.00	-0.57	8.16	1513	4251.98***	36.77***

Equipment (BusEq); Telephone and Television Transmission (Telcm); Utilities (Utils); Wholesale, Retail, and Some Services (Shops); Healthcare, Medical Equipment, and Drugs (Hlth); and Finance (Money). We collect VW daily sector returns, constructed from returns of US firms incorporated in the corresponding sector, from [Kenneth R. French's data library](#). Next, to match the frequency of commodity return data, we calculate weekly stock sector returns from the implicit daily index spanning from January 1, 1991 to December 31, 2019.

The upper part of Table 3.2 presents the descriptive statistics of re-

turn series for the commodity indices and the WTI oil price. Among five commodity indices, the highest mean return belongs to the SummerHaven Dynamic Commodity Index (SDCI) with 0.17% weekly or about 9% annual return. Meanwhile, the Bloomberg Commodity Index (BCOM) obtains the lowest weekly return that is 0.04% or roughly 2% per year. Interestingly, these two series hold among the lowest volatility. This finding indicates that the difference in index construction might cause a considerable variation in index properties. Conversely, the WTI oil price generates a relatively low return with the highest volatility. Given everything else being equal, investing in commodity indices sounds more optimal than in crude oil.

The lower part of Table 3.2 further presents the descriptive statistics of return series for US equity sectors. In general, US equity segments yield higher returns than commodities over the sample period. The best performing sector is Business Equipment (BusEq) with the weekly return of 0.23% or roughly 12% annual return whereas the Consumer Durables (Durbl) and Telephone and Television Transmission (Telcm) exhibit the lowest returns that is 0.15% per week or 8% per annual.

Regarding other statistics, skewness coefficients are negative for all cases. These coefficients imply that all data series skew to the left and tend to demonstrate more extreme negative than positive values. Kurtosis coefficients are typically different from three, indicating that returns are not normally distributed. Results from the Jarque–Bera test further confirm the presence of abnormality in return data at the

1% significance level. Finally, the LM-statistics present strong evidence of ARCH effects in the residuals for all return series. These features provide a motivation for a GARCH-class to model the volatility and transmission across two markets.

3.4 Empirical Results

In this section, we first present the main finding on the volatility spillovers between the commodity market and US equity sectors. Then, we construct the hedge ratios and optimal weights for portfolio pairs of commodity indices and stock sectors, based on results of the bivariate BEKK-GARCH(1,1) model. Finally, we demonstrate the economic implications for investors by comparing the effectiveness of the diversification strategies using commodity indices and crude oil.

3.4.1 Volatility spillovers across two markets

Table 3.3 presents the estimation results of the bivariate BEKK-GARCH(1,1) model for the conditional mean and variance of US sector returns in the pair with commodity index returns. To begin with, we examine the conditional mean equations of stock sector returns across all panels. The coefficients on one-period lagged stock returns, denoted by AR(1), are statistically negative for many sectors, such as Consumer Non-durables (NonDur); Telephone and Television Transmission (Telcm); and Wholesale, Retail, and Some Services (Shops). These coefficients provide evidence of short-term return predictability in a few sectors.

Table 3.3: Estimates for conditional mean/variance of US sector returns

The table presents the estimation results of the bivariate BEKK-GARCH(1,1) model for the conditional mean r_{t+1}^S and variance h_{t+1}^S of US sector returns in the pair with commodity index returns. The superscripts a, b, and c indicate significance at the 1%, 5%, and 10%, respectively.

Portfolio	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money
Panel A: Bloomberg Commodity Index (BCOM): January 1991 - December 2019											
<i>Conditional Mean Equation for r_{t+1}^S</i>											
Const	0.266 ^a	0.252 ^a	0.339 ^a	0.254 ^a	0.302 ^a	0.319 ^a	0.294 ^a	0.267 ^a	0.317 ^a	0.278 ^a	0.349 ^a
AR(1)	-0.090 ^a	0.000	-0.049 ^c	-0.064 ^b	-0.043	-0.059 ^b	-0.073 ^a	-0.028	-0.079 ^a	-0.062 ^b	-0.070 ^b
<i>Conditional Variance Equation for h_{t+1}^S</i>											
Const	0.754 ^a	0.991 ^a	0.751 ^a	0.862 ^a	0.589 ^a	0.336 ^a	0.522 ^a	0.601 ^a	0.575 ^a	0.820 ^a	0.548 ^a
$(\varepsilon_t^S)^2$	0.325 ^a	0.345 ^a	0.381 ^a	0.350 ^a	0.350 ^a	0.255 ^a	0.371 ^a	0.406 ^a	0.365 ^a	0.395 ^a	0.360 ^a
h_t^S	0.838 ^a	0.869 ^a	0.858 ^a	0.847 ^a	0.886 ^a	0.960 ^a	0.903 ^a	0.853 ^a	0.898 ^a	0.847 ^a	0.913 ^a
$(\varepsilon_t^C)^2$	0.082 ^a	0.176 ^a	0.123 ^a	0.063	0.053 ^a	0.059 ^b	0.046 ^c	0.068 ^a	0.028	0.041 ^a	0.011
h_t^C	0.013	0.004	0.017	0.084 ^a	0.010	-0.012 ^c	0.003	0.027 ^b	-0.003	0.005	0.006
Panel B: Thomson Reuters/CoreCommodity Index (CRB): January 1994 - December 2019											
<i>Conditional Mean Equation for r_{t+1}^S</i>											
Const	0.278 ^a	0.212 ^a	0.340 ^a	0.287 ^a	0.287 ^a	0.336 ^a	0.293 ^a	0.273 ^a	0.301 ^a	0.283 ^a	0.345 ^a
AR(1)	-0.082 ^a	0.001	-0.044	-0.068 ^b	-0.035	-0.063 ^b	-0.077 ^a	-0.019	-0.068 ^b	-0.066 ^b	-0.071 ^b
<i>Conditional Variance Equation for h_{t+1}^S</i>											
Const	0.507 ^a	0.894 ^a	0.590 ^a	0.848 ^a	0.327 ^a	0.302 ^a	0.403 ^a	0.662 ^a	0.458 ^a	0.488 ^a	0.518 ^a
$(\varepsilon_t^S)^2$	0.301 ^a	0.343 ^a	0.322 ^a	0.365 ^a	0.247 ^a	0.252 ^a	0.326 ^a	0.430 ^a	0.309 ^a	0.309 ^a	0.355 ^a
h_t^S	0.897 ^a	0.885 ^a	0.910 ^a	0.834 ^a	0.954 ^a	0.963 ^a	0.932 ^a	0.834 ^a	0.925 ^a	0.925 ^a	0.918 ^a
$(\varepsilon_t^C)^2$	0.139 ^a	0.171 ^a	0.152 ^a	0.053	0.066 ^a	0.066 ^a	0.049 ^b	0.047 ^b	0.119 ^a	0.070 ^a	0.074 ^b
h_t^C	-0.044 ^a	-0.019	-0.047 ^a	0.103 ^a	-0.015 ^b	-0.019 ^b	-0.013	0.041 ^a	-0.058 ^a	-0.022 ^b	-0.020
Panel C: Dow Jones Commodity Index (DJCI): January 1999 - December 2019											
<i>Conditional Mean Equation for r_{t+1}^S</i>											
Const	0.237 ^a	0.192 ^a	0.325 ^a	0.244 ^a	0.289 ^a	0.301 ^a	0.243 ^a	0.261 ^a	0.300 ^a	0.228 ^a	0.295 ^a
AR(1)	-0.088 ^b	-0.006	-0.060	-0.047	-0.056 ^c	-0.058 ^c	-0.070 ^b	-0.048	-0.079 ^b	-0.063 ^c	-0.076 ^b
<i>Conditional Variance Equation for h_{t+1}^S</i>											
Const	0.837 ^a	-0.976 ^a	0.661 ^a	1.055 ^a	0.609 ^a	0.336 ^a	0.441 ^a	0.742 ^a	0.421 ^a	0.925 ^a	0.503 ^a
$(\varepsilon_t^S)^2$	0.383 ^a	0.376 ^a	0.367 ^a	0.369 ^a	0.412 ^a	0.273 ^a	0.356 ^a	0.471 ^a	0.313 ^a	0.472 ^a	0.352 ^a
h_t^S	0.748 ^a	0.870 ^a	0.891 ^a	0.811 ^a	0.861 ^a	0.956 ^a	0.918 ^a	0.807 ^a	0.930 ^a	0.779 ^a	0.923 ^a
$(\varepsilon_t^C)^2$	0.176 ^a	0.153 ^a	0.109 ^a	0.061	0.044 ^a	0.047 ^b	0.073 ^a	0.050 ^c	0.113 ^a	0.063 ^a	-0.017
h_t^C	0.008	-0.015	-0.020	0.109 ^a	0.010	-0.015 ^c	-0.019	0.035 ^b	-0.052 ^a	0.008	0.004
Panel D: Rogers International Commodity Index (RICI): August 1998 - December 2019											
<i>Conditional Mean Equation for r_{t+1}^S</i>											
Const	0.243 ^a	0.194 ^b	0.331 ^a	0.251 ^a	0.281 ^a	0.305 ^a	0.261 ^a	0.256 ^a	0.305 ^a	0.224 ^a	0.303 ^a
AR(1)	-0.087 ^a	0.003	-0.054 ^c	-0.048	-0.051 ^c	-0.059 ^c	-0.071 ^b	-0.038	-0.074 ^b	-0.064 ^c	-0.076 ^b
<i>Conditional Variance Equation for h_{t+1}^S</i>											
Const	0.574 ^a	0.976 ^a	0.662 ^a	1.041 ^a	0.461 ^a	0.335 ^a	0.404 ^a	0.733 ^a	0.464 ^a	0.858 ^a	0.562 ^a
$(\varepsilon_t^S)^2$	0.330 ^a	0.376 ^a	0.354 ^a	0.397 ^a	0.340 ^a	0.269 ^a	0.334 ^a	0.471 ^a	0.308 ^a	0.454 ^a	0.372 ^a
h_t^S	0.872 ^a	0.868 ^a	0.896 ^a	0.827 ^a	0.915 ^a	0.956 ^a	0.930 ^a	0.811 ^a	0.925 ^a	0.808 ^a	0.911 ^a
$(\varepsilon_t^C)^2$	0.132 ^a	0.159 ^a	0.132 ^a	-0.005	0.048 ^a	0.056 ^b	0.044 ^b	0.039 ^c	0.113 ^a	0.067 ^a	0.038
h_t^C	-0.048 ^a	-0.024	-0.041 ^a	0.068 ^a	-0.012	-0.015 ^b	-0.016 ^c	0.029 ^c	-0.053 ^a	-0.019	-0.011
Panel E: SummerHaven Dynamic Commodity Index (SDCI): January 1991 - December 2019											
<i>Conditional Mean Equation for r_{t+1}^S</i>											
Const	0.258 ^a	0.249 ^a	0.335 ^a	0.207 ^a	0.293 ^a	0.325 ^a	0.291 ^a	0.260 ^a	0.314 ^a	0.287 ^a	0.343 ^a
AR(1)	-0.097 ^a	-0.003	-0.056 ^b	-0.054 ^b	-0.053 ^b	-0.063 ^c	-0.079 ^a	-0.033	-0.065 ^b	-0.060 ^b	-0.069 ^b
<i>Conditional Variance Equation for h_{t+1}^S</i>											
Const	0.686 ^a	0.834 ^a	0.599 ^a	0.850 ^a	0.400 ^a	0.346 ^a	0.482 ^a	0.531 ^a	0.448 ^a	0.595 ^a	0.521 ^a
$(\varepsilon_t^S)^2$	0.330 ^a	0.309 ^a	0.338 ^a	0.355 ^a	0.280 ^a	0.258 ^a	0.348 ^a	0.396 ^a	0.300 ^a	0.333 ^a	0.347 ^a
h_t^S	0.851 ^a	0.904 ^a	0.905 ^a	0.860 ^a	0.939 ^a	0.959 ^a	0.916 ^a	0.879 ^a	0.931 ^a	0.907 ^a	0.919 ^a
$(\varepsilon_t^C)^2$	-0.114 ^a	0.185 ^a	0.055 ^b	0.020	0.015	0.057 ^a	0.018	0.019	0.098 ^a	0.038 ^b	-0.035
h_t^C	0.069 ^a	-0.040 ^b	0.009	0.081 ^a	0.007	-0.012 ^b	0.009	0.022 ^b	-0.035 ^a	-0.001	0.026 ^a

Given other factors constant, this finding indicates a reversal of stock sector returns, in which an increase in this week returns signals a decrease in next week returns. In contrast, past stock returns are not useful in predicting future stock returns in some other sectors, such as Consumer Durables (Durbl); Chemicals and Allied Products (Chems); and Utilities (Utils).

The conditional variance equations in Table 3.3 present results of stock's own conditional ARCH and GARCH effects, corresponding to $(\varepsilon_t^S)^2$ and h_t^S , and volatility spillovers from commodity indices to stock sector returns, corresponding to $(\varepsilon_t^C)^2$ and h_t^C . Specifically, coefficients on the squared error terms $(\varepsilon_t^S)^2$ and $(\varepsilon_t^C)^2$ represent the effect of recent shocks or news, whereas coefficients on the lagged conditional variance h_t^S and h_t^C represent the effect of past volatility, originating from equity and commodity markets to equity sectors.

Across all panels and all sectors, the estimated coefficients on stock's own conditional ARCH and GARCH effects are statistically significant at the 1% level. Our finding suggests that changes in the conditional volatility of stock sector returns depend strongly on both recent and past own shocks. In addition, the estimated coefficients on the ARCH effects are smaller than their corresponding coefficients on the GARCH effects, indicating that the dependence of stock sector volatility on its past volatility is stronger than on its recent shocks. Furthermore, the sum of two respective coefficients is greater than unity in most cases. Note that the sum of these elements that is greater than one does not validate the condition for a stationary process. According to

Engle and Kroner (1995), the sum of diagonal elements in stationary unrestricted BEKK-GARCH models could exceed one.

The results on volatility spillovers from commodity indices to equity sectors across five panels are somewhat mixed. In Panels A and C, we observe more statistically significant coefficients on the ARCH than the GARCH effects. These numbers indicate that in general, the conditional volatility of stock sector returns is strongly affected by the recent unexpected shocks in Bloomberg and Dow Jones commodity indices. Meantime, past volatility of these indices exhibits limited impact on the US equity sectors. Conversely, Panels B, D, and E provide evidence of both ARCH and GARCH effects, which transmit from the respective commodity indices to equity sectors. In particular, an unexpected shock in the Thomson Reuters/CoreCommodity, Rogers International, or SummerHaven Dynamic Commodity Index increases the volatility of the US stock sectors, and these effects are persistent in the long-run. The mixed results in volatility transmission from different commodity indices to equity sectors might exist because of the difference in commodity index construction and the time period being investigated.

Interestingly, unlike other sectors examined, Oil, Gas, and Coal Extraction and Products (Energy) and Finance (Money) sectors respond differently to the commodity shocks over time. While other sectors tend to respond to recent or both types of commodity shocks, the energy sector is strongly affected by the past commodity shocks (significant coefficient on h_t^C), but not the recent shocks, as evidenced

by the insignificant coefficient on $(\varepsilon_t^C)^2$. The highly effective hedging strategy of the energy sector against the commodity price shocks in the short-term is the most likely explanation for this finding. For the financial sector, we detect no strong evidence of both short- and long-term volatility transmissions from the commodity market. The insensitivity of the financial sector to the commodity shocks is justifiable because the financial sector is not a typical industrial segment that uses commodity-related products as inputs or outputs. This fact is indeed consistent with the finding by Malik and Ewing (2009), which reveals that the financial sector exhibits the least volatile response to the oil shocks among all examined sectors.

Finally, we investigate volatility spillovers from US equity sectors to commodity indices. Table 3.4 presents the estimation results of the bivariate BEKK-GARCH(1,1) model for the conditional mean and variance of commodity index returns in the pair with US sector returns. In Panels A and E, we do not find evidence supporting this direction. Specifically, Bloomberg and SummerHaven Dynamic commodity indices do not respond to both recent and past US equity shocks. Meanwhile, other commodity indices in Panels B, C, and D are strongly affected by shocks from the equity market. Together with findings from Table 3.3, this result demonstrates a unidirectional transmission from Bloomberg and SummerHaven Dynamic commodity indices and a bidirectional spillover from other commodity indices to US equity segments. Because commodity indices are more likely diversified, these indices are less influenced by equity shocks. Thus, our

Table 3.4: Estimates for conditional mean/variance of commodity index returns

The table presents the estimation results of the bivariate BEKK-GARCH(1,1) model for the conditional mean r_{t+1}^C and variance h_{t+1}^C of commodity index returns in the pair with US sector returns. The superscripts a, b, and c indicate significance at the 1%, 5%, and 10%, respectively.

Portfolio	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money
Panel A: Bloomberg Commodity Index (BCOM): January 1991 - December 2019											
<i>Conditional Mean Equation for r_{t+1}^C</i>											
Const	0.063	0.063	0.067	0.070 ^c	0.055	0.050	0.055	0.052	0.038	0.054	0.049
AR(1)	-0.001	0.014	0.007	-0.006	0.006	0.001	0.001	0.005	0.002	0.006	0.002
<i>Conditional Variance Equation for h_{t+1}^C</i>											
Const	0.167 ^a	0.170 ^a	0.170 ^a	0.166 ^a	0.165 ^a	0.161 ^a	0.182 ^a	0.176 ^a	0.155 ^a	0.162 ^a	0.160 ^a
$(\varepsilon_t^C)^2$	0.225 ^a	0.239 ^a	0.235 ^a	0.208 ^a	0.225 ^a	0.231 ^a	0.226 ^a	0.200 ^a	0.232 ^a	0.225 ^a	0.221 ^a
h_t^C	0.968 ^a	0.967 ^a	0.967 ^a	0.952 ^a	0.970 ^a	0.969 ^a	0.967 ^a	0.955 ^a	0.969 ^a	0.970 ^a	0.972 ^a
$(\varepsilon_t^S)^2$	0.003	-0.008	-0.008	-0.018	0.001	-0.006	-0.010	-0.071	-0.006	-0.017	0.009
h_t^S	0.006	0.000	0.003	0.027 ^b	0.001	0.001	0.010	0.055	-0.005	0.008	-0.003
Panel B: Thomson Reuters/CoreCommodity Index (CRB): January 1994 - December 2019											
<i>Conditional Mean Equation for r_{t+1}^C</i>											
Const	0.134 ^a	0.120 ^b	0.122 ^b	0.158 ^a	0.120 ^b	0.121 ^b	0.102 ^b	0.123 ^b	0.101 ^b	0.111 ^b	0.122 ^b
AR(1)	-0.016	0.003	-0.005	-0.011	-0.010	-0.009	-0.009	-0.003	-0.007	-0.008	-0.013
<i>Conditional Variance Equation for h_{t+1}^C</i>											
Const	0.260 ^a	0.293 ^a	0.269 ^a	0.311 ^a	0.223 ^a	0.223 ^a	0.234 ^a	0.282 ^a	0.253 ^a	0.249 ^a	0.263 ^a
$(\varepsilon_t^C)^2$	0.297 ^a	0.257 ^a	0.272 ^a	0.209 ^a	0.230 ^a	0.236 ^a	0.216 ^a	0.197 ^a	0.306 ^a	0.251 ^a	0.238 ^a
h_t^C	0.941 ^a	0.958 ^a	0.951 ^a	0.919 ^a	0.966 ^a	0.964 ^a	0.968 ^a	0.953 ^a	0.925 ^a	0.957 ^a	0.962 ^a
$(\varepsilon_t^S)^2$	0.075 ^b	0.008	0.033 ^c	-0.033	0.042 ^b	0.012	0.045 ^a	-0.049 ^c	0.050 ^b	0.050 ^b	0.024
h_t^S	-0.058 ^a	-0.006	-0.018 ^c	0.054 ^a	-0.016 ^b	-0.005	-0.018 ^a	0.046 ^a	-0.033 ^a	-0.027 ^a	-0.011
Panel C: Dow Jones Commodity Index (DJCI): January 1999 - December 2019											
<i>Conditional Mean Equation for r_{t+1}^C</i>											
Const	0.153 ^a	0.099 ^c	0.115 ^b	0.146 ^b	0.120 ^b	0.120 ^b	0.131 ^b	0.115 ^b	0.102 ^c	0.112 ^c	0.077
AR(1)	0.002	0.016	0.006	0.016	0.011	0.002	0.005	0.009	0.003	0.011	0.007
<i>Conditional Variance Equation for h_{t+1}^C</i>											
Const	0.183	0.229 ^a	0.218 ^a	0.237 ^a	0.255 ^a	0.221 ^a	0.312 ^a	0.249 ^a	0.238 ^a	0.225 ^a	0.211 ^a
$(\varepsilon_t^C)^2$	0.257 ^a	0.246 ^a	0.242 ^a	0.203 ^a	0.229 ^a	0.237 ^a	0.249 ^a	0.206 ^a	0.305 ^a	0.237 ^a	0.204 ^a
h_t^C	0.967 ^a	0.965 ^a	0.965 ^a	0.955 ^a	0.967 ^a	0.964 ^a	0.955 ^a	0.958 ^a	0.931 ^a	0.968 ^a	0.973 ^a
$(\varepsilon_t^S)^2$	0.055	0.040 ^b	0.057 ^a	-0.009	0.021	0.015	-0.006	-0.047 ^c	0.056 ^a	0.034	0.047 ^a
h_t^S	-0.047	-0.022 ^b	-0.029 ^a	0.020	-0.009	-0.005	0.008	0.042 ^a	-0.028 ^a	-0.028	-0.017 ^a
Panel D: Rogers International Commodity Index (RICI): August 1998 - December 2019											
<i>Conditional Mean Equation for r_{t+1}^C</i>											
Const	0.112 ^c	0.090	0.111 ^c	0.123 ^b	0.100	0.118 ^c	0.080	0.114 ^c	0.093	0.094	0.093
AR(1)	-0.010	0.005	-0.004	-0.001	-0.009	-0.009	-0.006	0.000	-0.005	-0.003	-0.011
<i>Conditional Variance Equation for h_{t+1}^C</i>											
Const	0.250 ^a	0.254 ^a	0.235 ^a	0.188 ^a	0.240 ^a	0.240 ^a	0.233 ^a	0.324 ^a	0.240 ^a	0.251 ^a	0.256 ^a
$(\varepsilon_t^C)^2$	0.316 ^a	0.256 ^a	0.269 ^a	0.219 ^a	0.233 ^a	0.237 ^a	0.220 ^a	0.203 ^a	0.313 ^a	0.255 ^a	0.229 ^a
h_t^C	0.931 ^a	0.963 ^a	0.953 ^a	0.985 ^a	0.966 ^a	0.964 ^a	0.966 ^a	0.955 ^a	0.923 ^a	0.959 ^a	0.966 ^a
$(\varepsilon_t^S)^2$	0.115 ^a	0.040 ^c	0.058 ^a	0.016	0.065 ^b	0.018	0.065 ^a	-0.059 ^b	0.071 ^a	0.066 ^b	0.037 ^c
h_t^S	-0.094 ^a	-0.028 ^c	-0.035 ^a	-0.025 ^c	-0.031 ^a	-0.008 ^c	-0.025 ^a	0.053 ^a	-0.043 ^a	-0.059 ^a	-0.019 ^b
Panel E: SummerHaven Dynamic Commodity Index (SDCI): January 1991 - December 2019											
<i>Conditional Mean Equation for r_{t+1}^C</i>											
Const	0.081 ^b	0.111 ^a	0.113 ^a	0.121 ^a	0.100	0.115 ^a	0.118 ^a	0.113 ^a	0.111 ^a	0.115	0.112 ^a
AR(1)	0.036	0.038	0.030	0.025	0.026	0.032	0.033	0.032	0.028	0.027	0.022
<i>Conditional Variance Equation for h_{t+1}^C</i>											
Const	0.156 ^a	0.250 ^a	0.218 ^a	0.175 ^a	0.201 ^a	0.204 ^a	0.206 ^a	0.183 ^a	0.229 ^a	0.209 ^a	0.194 ^a
$(\varepsilon_t^C)^2$	0.240 ^a	0.271 ^a	0.252 ^a	0.216 ^a	0.243 ^a	0.249 ^a	0.236 ^a	0.213 ^a	0.291 ^a	0.240 ^a	0.240 ^a
h_t^C	0.966 ^a	0.951 ^a	0.959 ^a	0.957 ^a	0.963 ^a	0.961 ^a	0.961 ^a	0.961 ^a	0.945 ^a	0.963 ^a	0.963 ^a
$(\varepsilon_t^S)^2$	0.005	-0.001	-0.004	0.001	0.001	-0.012	-0.019 ^c	-0.045 ^a	-0.005	-0.009	-0.005
h_t^S	-0.007	0.001	0.002	0.014	-0.001	0.003	0.012 ^b	0.031 ^a	-0.006	0.003	0.003

results seem reasonable, though slightly different from the previous literature that finds a strong bidirectional volatility spillover between oil and US equity sectors.

To summarize, this section establishes the presence of volatility spillovers across the commodity and US equity markets and that the transmission is stronger from commodities to stocks than from stocks to commodities. As an implication, this section emphasizes the importance of hedging strategies for the US equity sectors toward the commodity shocks. Furthermore, while not being examined in this chapter, findings of this section reveal the possibility of forecasting future stock volatility using current commodity index volatility.

3.4.2 Hedge ratios and optimal weights in the portfolio pairs

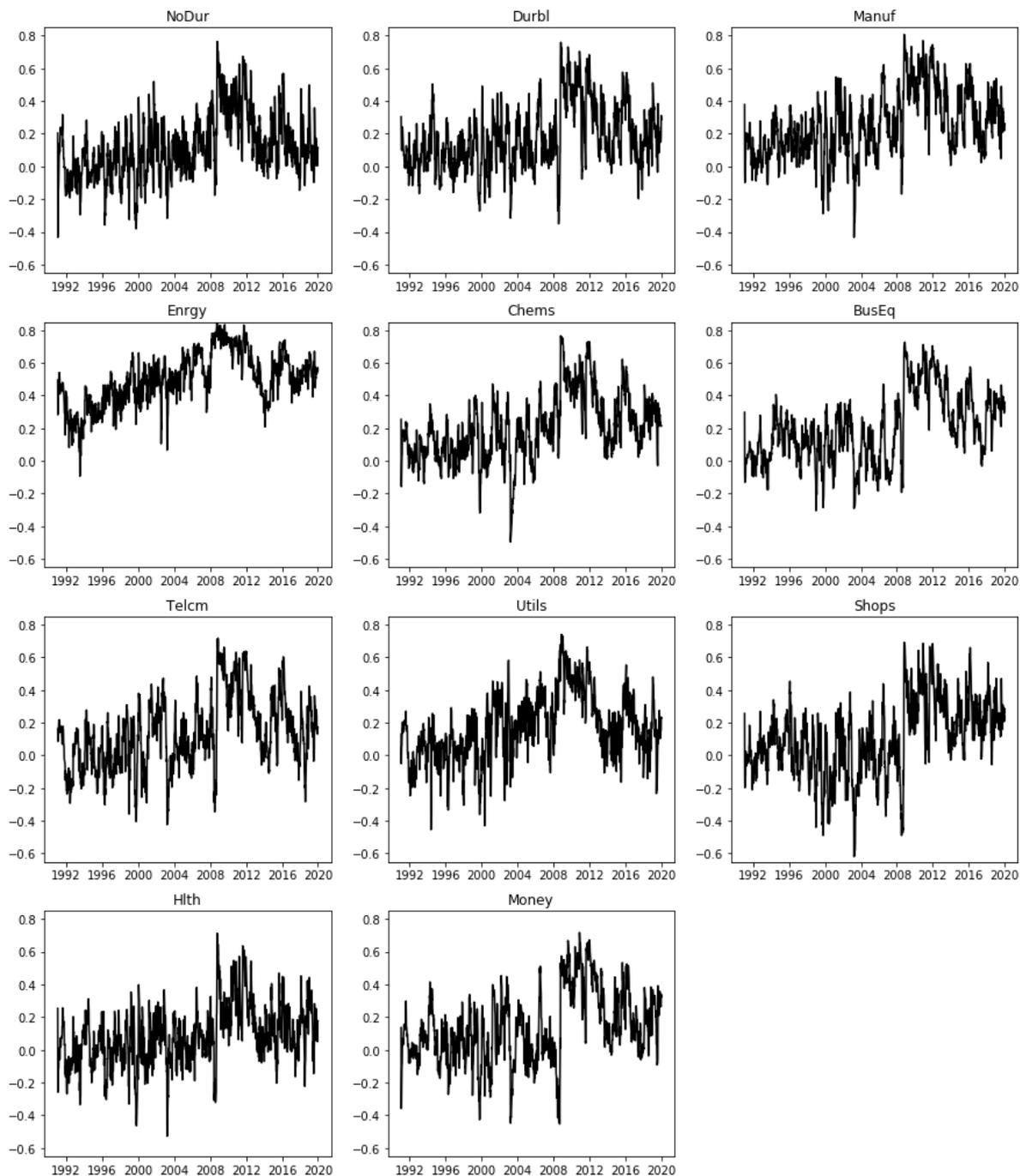
Next, we use results from the previous section to construct the hedge ratios and optimal weights for equity sectors in the portfolio pairs with commodity indices. First, we calculate the conditional correlation between equity segments and each of five commodity indices at time t as follows:

$$\rho_t = \frac{h_t^{SC}}{\sqrt{h_t^S h_t^C}},$$

where h_t^S , h_t^C , and h_t^{SC} are the conditional variance of the stock sector, the commodity index, and the conditional covariance between two variables at time t , respectively. These parameters are estimated through Equation (3.3).

Figure 3.1: Average correlations between commodity indices and equity sectors

The figure plots the conditional correlations between commodity indices and equity sectors, which is averaged across indices over time. The sample period is from January 1991 to December 2019.



Then, we average the correlations across commodity indices. Figure 3.1 plots the average conditional correlations between commodity indices and equity sectors over time. Figure 3.1 shows a clear pattern that the conditional correlations between each pair of series are time-

varying. Before 2008, no trend in the correlations exists. However, during the global financial crisis of 2008 and 2009, these conditional correlations hit their highest values of approximately 0.8. Because the systematic risks tend to increase significantly in the crisis, the high magnitude of the conditional correlations between commodity indices and equity during this time is expected and in line with the finding of the previous literature (See eg. Filis, Degiannakis, and Floros (2011); Creti, Joets, and Mignon (2013); Kolodziej, Kaufmann, Kulatilaka, Bicchetti, and Maystre (2014); Bhardwaj, Gorton, and Rouwenhorst (2016); and Junttila, Pesonen, and Raatikainen (2018)). The conditional correlations then decline in 2013 before increasing and remaining high, most likely due to the global commodity price collapse between mid-2014 and early 2016.

Furthermore, the conditional correlations between commodity indices and equity vary across segments. In particular, the dynamic correlations between commodity indices and the energy sector are highly positive most of the time. This fact indicates a limited opportunity for portfolio diversification between these two datasets. Conversely, the conditional correlations between commodity indices and Consumer Nondurables (NonDur); Wholesale, Retail, and Some Services (Shops); and Healthcare, Medical Equipment, and Drugs (Hlth) are relatively low, ranging from -0.5 to 0.6. The periods of negative correlations, especially before the crisis, offer great scope for meaningful portfolio diversification.

Overall, Figure 3.1 shows that the dynamic conditional correlations

provide more useful information than the constant unconditional correlations do. Thus, analyzing the correlation between two series via a dynamic GARCH-class model is advisable. Given the information on the dynamic conditional correlation, Kroner and Sultan (1993) further suggest using the following formula to compute the optimal hedge ratio for the portfolio of commodity indices and equity sectors. β_t^C indicates the optimal number of commodity indices that need to be sold to hedge a long position on the equity segment.

$$\beta_t^C = \frac{h_t^{SC}}{h_t^C} = \rho_t \sqrt{\frac{h_t^S}{h_t^C}}$$

In addition, Kroner and Ng (1998) recommend computing the optimal weights w_t^C of commodity indices in the portfolio as follows:

$$w_t^C = \frac{h_t^S - h_t^{SC}}{h_t^S - 2h_t^{SC} + h_t^C},$$

under the constraint that

$$w_t^C = \begin{cases} 0 & \text{if } w_t^C < 0 \\ w_t^C & \text{if } 0 \leq w_t^C \leq 1 \\ 1 & \text{if } w_t^C > 1 \end{cases}$$

The weight of the stock sector is $(1 - w_t^C)$, accordingly.

Table 3.5 presents the average hedge ratios and optimal weights of commodity indices in portfolio pairs with US equity sectors over the sample period. First, Panel A of Table 3.5 shows that the average hedge ratios vary across sectors, indicating large variations in

Table 3.5: Hedge ratios and optimal weights of commodity indices in portfolios

The table presents the average hedge ratios and optimal weights of commodity indices in portfolio pairs with US equity sectors over the sample period. The commodity indices are the Bloomberg Commodity Index (BCOM), Thomson Reuters/CoreCommodity Index (CRB), Dow Jones Commodity Index (DJCI), Rogers International Commodity Index (RICI), and SummerHaven Dynamic Commodity Index (SDCI). The longest sample period is from January 1, 1991 to December 31, 2019.

Portfolio	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money
Panel A: Optimal hedge ratios of commodity indices in portfolio pairs											
BCOM	0.089	0.281	0.318	0.751	0.196	0.286	0.142	0.168	0.098	0.075	0.185
CRB	0.102	0.298	0.334	0.772	0.194	0.305	0.178	0.181	0.104	0.097	0.209
DJCI	0.149	0.395	0.441	0.880	0.278	0.377	0.258	0.246	0.157	0.149	0.289
RICI	0.129	0.340	0.370	0.815	0.230	0.311	0.218	0.205	0.126	0.128	0.238
SDCI	0.099	0.299	0.358	0.721	0.234	0.328	0.153	0.174	0.103	0.103	0.189
Panel B: Optimal weights of commodity indices in portfolio pairs											
BCOM	0.473	0.767	0.661	0.843	0.535	0.729	0.601	0.501	0.588	0.590	0.677
CRB	0.397	0.729	0.622	0.820	0.477	0.687	0.560	0.457	0.522	0.527	0.635
DJCI	0.401	0.774	0.674	0.884	0.484	0.680	0.580	0.495	0.537	0.528	0.667
RICI	0.327	0.710	0.592	0.793	0.414	0.615	0.511	0.418	0.466	0.470	0.601
SDCI	0.520	0.805	0.720	0.867	0.599	0.775	0.653	0.560	0.637	0.638	0.721

the hedging costs for equity segments. For the Consumer Nondurables (NonDur); Wholesale, Retail, and Some Services (Shops); and Healthcare, Medical Equipment, and Drugs (Hlth) sectors, the hedge ratios are typically low, suggesting good hedging effectiveness involving commodity indices in these sectors. Specifically, a \$1 long position in these mentioned sectors can be hedged by 8 to 15 cents short position in commodity indices. On the other end of the spectrum, the average hedge ratio for the energy sector is the highest, ranging from 0.72 to 0.88. Consistent with the previous conditional correlation analysis, this result indicates that hedging energy stocks using commodity indices is the most expensive.

Second, in general, the hedging costs using the Bloomberg (BCOM) and SummerHaven Dynamic Commodity Index (SDCI) are among the lowest. This finding is consistent with the results from Table 3.4.

Because Bloomberg and SummerHaven Dynamic commodity indices do not respond to both recent and past US equity shocks, these indices are less correlated with equity, which, in turn, lowers the hedging costs.

Third, in Panel B, we observe significant cross-sector variations in the optimal weights. By sector, the average optimal weight for commodity indices ranges from 45.2% (Consumer Nondurables) to 83.8% (Energy). These numbers indicate that for a one-dollar portfolio pair, investors should invest from approximately 45 cents to 84 cents in commodity indices. As an implication, investors should hold fewer stocks than commodity in their portfolio pairs most of the time to minimize the risk exposure. This result appears consistent with the fact that equity sector returns are more volatile than commodity index returns.

Finally, we should emphasize that while the statistics in Table 3.5 reveal important insights about the average hedge ratios and optimal portfolio weights of various diversification strategies, they do not reflect the whole picture. Figures B.1 and B.2 in the Appendix provide more detail on the time-varying patterns of these variables over the sample period.

In summary, this section shows how investors could use the results from the BEKK-GARCH model to make their optimal hedging and portfolio allocation decisions. In the next section, we examine the effectiveness of these diversification strategies.

3.4.3 Diversification and hedging effectiveness

In this section, we attempt to construct the diversification strategy using the optimal weights previously calculated for the commodity-equity portfolio pairs. Furthermore, we apply the same method to construct the corresponding strategy for the pairs of WTI crude oil and equity sectors. The central aim for investors following these strategies is to minimize the risk exposure while maintaining the portfolio returns. Thus, by comparing the performance of these strategies regarding the risk-adjusted returns and the hedging effectiveness, we demonstrate the economic implications for investors. Following Ku, Chen, and Chen (2007), we define the hedging effectiveness as follows:

$$HE = \frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}}$$

where the unhedged portfolio is the portfolio of 100% equity and the hedged portfolio is the weighted portfolio pairs of equity and commodity indices/oil. In general, a large hedging effectiveness index indicates a better diversification strategy, given a same level of returns.

Table 3.6 compares the effectiveness of the diversification strategies for equity sectors using commodity indices and crude oil over the sample period. At first glance, Table 3.6 shows that the diversification strategies using WTI oil generate higher mean returns in many cases. However, these strategies are also more volatile than the ones involving commodity indices. Thus, after we adjust the risk, returns of the commodity-equity portfolio pairs are higher most of the time.

On average, these results indicate that adding commodity indices to equity sectors is preferable in terms of the risk-adjusted returns.

Then, we compare the hedging effectiveness (HE) of the two strategies. On the one hand, strategies involving WTI oil is associated with between 2.3% and 29.3% risk reduction, depending on the segment and the time period being investigated. Meanwhile, when we only consider the strategies using the Rogers International Commodity Index (RICI) that offer the lowest HE among those using indices, the variance reduction ranges from 24.2% (Consumer Nondurables) to 64% (Business Equipment). Results of the strategies using the Summer-Haven Dynamic Commodity Index (SDCI) are even more pronounced with 46.2% and 72.5% risk reduction, respectively. This finding further confirms the outperformance of the strategy involving commodity indices over WTI oil with regard to the hedging effectiveness.

Taking two criterion, the risk-adjusted returns and hedging effectiveness, into account, our analysis suggests that strategies involving commodity indices often lead to additional diversification benefits relative to those using WTI crude oil. One possible explanation is that commodity indices are more diversified and less volatile than WTI crude oil, as evidenced by the descriptive statistics in Table 3.2. Thus, investors should consider using commodity indices instead of WTI crude oil to hedge and diversify the risks of their sectoral investments. Notably, this result is robust over all sample periods.

Table 3.6: Effectiveness of the diversification strategy for equity sectors

The table compares the risk-adjusted returns, measured by dividing each portfolio's mean return by its standard deviation, and the hedging effectiveness of the diversification strategies using commodity indices and crude oil over the sample period. The commodity indices are the Bloomberg Commodity Index (BCOM), Thomson Reuters/CoreCommodity Index (CRB), Dow Jones Commodity Index (DJCI), Rogers International Commodity Index (RICI), and SummerHaven Dynamic Commodity Index (SDCI).

Portfolio	Return/Risk Measures	Period: 1991-2019			Period: 1994-2019		Period: 1998-2019		Period: 1999-2019	
		BCOM	SDCI	Oil	CRB	Oil	RDCI	Oil	DJCI	Oil
NoDur	Mean	0.11	0.17	0.17	0.13	0.17	0.13	0.15	0.13	0.15
	Std. Dev.	1.40	1.34	1.72	1.49	1.72	1.59	1.76	1.53	1.74
	Mean/Std. Dev.	0.08	0.13	0.10	0.09	0.10	0.08	0.08	0.09	0.08
	HE	40.7%	46.2%	11.1%	31.6%	9.4%	24.2%	8.0%	27.6%	6.5%
Durbl	Mean	0.03	0.13	0.06	0.04	0.03	0.02	-0.01	0.05	0.00
	Std. Dev.	1.82	1.68	2.88	1.98	2.98	2.23	3.15	2.03	3.14
	Mean/Std. Dev.	0.02	0.08	0.02	0.02	0.01	0.01	0.00	0.02	0.00
	HE	69.2%	74.0%	23.1%	65.5%	21.6%	60.4%	21.2%	66.8%	20.6%
Manuf	Mean	0.08	0.16	0.14	0.10	0.13	0.09	0.10	0.10	0.10
	Std. Dev.	1.76	1.64	2.48	1.91	2.55	2.15	2.70	1.98	2.69
	Mean/Std. Dev.	0.05	0.10	0.05	0.05	0.05	0.04	0.04	0.05	0.04
	HE	54.2%	60.5%	10.0%	49.2%	9.5%	42.5%	8.8%	50.1%	8.2%
Enrgy	Mean	0.05	0.16	0.08	0.08	0.07	0.06	0.03	0.09	0.04
	Std. Dev.	1.96	1.79	2.93	2.14	3.02	2.39	3.20	2.16	3.20
	Mean/Std. Dev.	0.02	0.09	0.03	0.04	0.02	0.02	0.01	0.04	0.01
	HE	56.4%	63.4%	2.3%	51.2%	2.3%	45.5%	2.7%	55.4%	2.5%
Chems	Mean	0.09	0.16	0.17	0.12	0.16	0.10	0.13	0.11	0.13
	Std. Dev.	1.59	1.49	1.98	1.69	2.01	1.85	2.09	1.75	2.07
	Mean/Std. Dev.	0.06	0.10	0.08	0.07	0.08	0.05	0.06	0.06	0.06
	HE	42.9%	49.4%	11.3%	36.9%	10.7%	29.1%	9.7%	34.9%	9.1%
BusEq	Mean	0.09	0.17	0.18	0.13	0.18	0.12	0.14	0.13	0.14
	Std. Dev.	1.76	1.65	2.78	1.92	2.85	2.11	2.89	1.93	2.86
	Mean/Std. Dev.	0.05	0.11	0.06	0.07	0.06	0.06	0.05	0.07	0.05
	HE	71.7%	75.1%	29.6%	67.8%	29.3%	62.0%	28.6%	66.8%	27.4%
Telcm	Mean	0.08	0.16	0.13	0.10	0.12	0.09	0.09	0.10	0.07
	Std. Dev.	1.63	1.53	2.31	1.78	2.39	1.98	2.50	1.82	2.49
	Mean/Std. Dev.	0.05	0.10	0.06	0.06	0.05	0.04	0.04	0.05	0.03
	HE	59.4%	64.3%	18.7%	54.7%	18.5%	48.8%	18.9%	56.1%	18.3%
Utils	Mean	0.10	0.16	0.16	0.12	0.16	0.12	0.15	0.12	0.15
	Std. Dev.	1.56	1.48	2.01	1.68	2.06	1.84	2.19	1.73	2.21
	Mean/Std. Dev.	0.06	0.11	0.08	0.07	0.08	0.06	0.07	0.07	0.07
	HE	44.9%	50.8%	8.5%	40.7%	10.6%	35.8%	9.7%	43.6%	8.3%
Shops	Mean	0.10	0.17	0.18	0.12	0.17	0.12	0.16	0.12	0.15
	Std. Dev.	1.55	1.47	2.13	1.68	2.15	1.84	2.23	1.72	2.20
	Mean/Std. Dev.	0.06	0.12	0.08	0.07	0.08	0.07	0.07	0.07	0.07
	HE	57.0%	61.3%	18.7%	50.1%	17.9%	43.9%	17.5%	49.3%	16.5%
Hlth	Mean	0.09	0.16	0.17	0.12	0.18	0.09	0.14	0.10	0.13
	Std. Dev.	1.50	1.41	2.06	1.61	2.07	1.73	2.11	1.62	2.08
	Mean/Std. Dev.	0.06	0.11	0.08	0.07	0.09	0.05	0.07	0.06	0.06
	HE	58.0%	62.5%	20.0%	49.9%	17.1%	43.0%	15.6%	48.3%	15.3%
Money	Mean	0.07	0.15	0.13	0.09	0.11	0.05	0.05	0.07	0.07
	Std. Dev.	1.74	1.61	2.62	1.89	2.70	2.13	2.84	1.94	2.82
	Mean/Std. Dev.	0.04	0.09	0.05	0.05	0.04	0.02	0.02	0.03	0.02
	HE	66.1%	71.1%	23.5%	62.2%	22.9%	56.8%	23.2%	62.7%	21.6%

3.5 Conclusion

Using several commodity indices as proxies for the commodity market, this chapter investigates volatility transmission between commodities and major US equity sectors with implications for the risk management and portfolio allocation decisions. The main rationale for this particular study is, as we argue, that commodity indices might be better than crude oil in capturing the dynamic of the commodity market. Hence, using commodity indices as proxies for the market can eliminate potential bias. Furthermore, given an increasing trend of index investment in the commodity market, results from this chapter become even more important to investors and market participants, who are particularly interested in the diversification strategies across commodity indices and equity sectors.

Empirical results from the bivariate BEKK-GARCH model indicate a significant volatility spillover between commodity indices and US equity segments and that the transmission is stronger from commodities to stocks than from stocks to commodities. In addition, this chapter finds a heterogeneous intensity of volatility spillovers across sectors. Specifically, the majority of segments tend to respond to recent or both types of commodity shocks with varying intensities. Meanwhile, the energy sector is strongly affected by the past commodity shocks but not the recent shocks. Moreover, we detect no evidence of both short- and long-term volatility transmissions from the commodity market to the financial sector.

Second, the dynamic conditional correlations between commodity indices and equity vary substantially over time and sectors. This result further implies a considerable cross-sector variation in the hedging costs and optimal weights for the portfolio pair of commodities and equity. Interestingly, portfolio analysis suggests that investors in the US market should hold fewer stocks than commodity indices to minimize the risk exposure.

Equally significant, by examining the risk-adjusted returns and HE, we find that the strategies involving commodity indices often offer higher diversification benefits than those using WTI crude oil. As a recommendation, to hedge and diversify the risks of their sectoral investments, investors should use commodity indices instead of WTI crude oil.

Conclusion

This dissertation contributes to a better understanding of industry stock returns and volatility in the United States and provides significant practical implications for both long-term and short-term investors. Chapter 1 investigates (i) whether the long-term return predictive patterns hold across US industries and (ii) which hypothesis can explain the different predictive patterns, if any. Using data over the last 91 years, we confirm that value-weighted stock returns are predictable. Moreover, our work establishes a predictability heterogeneity over US industries, in which stock returns are more predictable in sectors with a large average firm size. In light of the dividend-smoothing hypothesis, we show that differences in dividend smoothness potentially drive cross-industry predictive patterns. The findings further suggest that dividend yields are not good proxies for predicting long-term returns in some small industries.

Chapter 2 uses monthly data from 1975 to 2019 to examine whether the ratio of gold to platinum prices (GP) leads US industry stock returns in-sample and out-of-sample over short and intermediate hori-

zons. We find that GP predicts cyclical industry excess returns better than defensive industry excess returns. This finding remains robust to several robustness checks, such as subsample analysis, alternative econometric method, and alternative classification of industry cyclicity. The one-month out-of-sample forecast by GP is weak but economically meaningful for mean-variance investors. As an illustration, a one-month GP-based trading strategy generates an average certainty equivalent return that is approximately 2.4% p.a. higher than the buy-and-hold strategy across all industries.

Using several commodity indices as proxies for the commodity market, chapter 3 establishes significant volatility transmission between commodities and major US equity sectors over the sample period from January 1991 to December 2019. Moreover, these volatility spillovers from commodities vary across sectors. These findings imply a considerable cross-sector variation in the hedging costs and optimal weights for the portfolio pair of commodities and equity. In the context of portfolio allocation, this chapter suggests that investors in the US market should hold less stocks than commodity indices to minimize the risk exposure. Finally, the strategies involving commodity indices often lead to additional diversification benefits relative to those using West Texas Intermediate crude oil.

Appendices



Appendix to Chapter 1

A.1 Delta-method Approximations for Mean and Variance of a Ratio

Consider two random variables X and Y with finite means $EX = \mu_x$ and $EY = \mu_y$. For any $f(X, Y)$, the first-order Taylor approximation functions for $E(f(X, Y))$ and $Var(f(X, Y))$ around the expansion

point $\theta = (\mu_x, \mu_y)$ are

$$\begin{aligned}
E(f(X, Y)) &\approx E[f(\theta) + f'_x(\theta)(X - \mu_x) + f'_y(\theta)(Y - \mu_y)] \\
&= E[f(\theta)] + E[f'_x(\theta)(X - \mu_x)] + E[f'_y(\theta)(Y - \mu_y)] \\
&= E[f(\theta)] + 0 + 0 \\
&= f(\mu_x, \mu_y)
\end{aligned}$$

$$\begin{aligned}
Var(f(X, Y)) &= E[f(X, Y) - E(f(X, Y))]^2 \\
&\approx E[f(\theta) + f'_x(\theta)(X - \mu_x) + f'_y(\theta)(Y - \mu_y) - f(\theta)]^2 \\
&= E[f'_x(\theta)(X - \mu_x) + f'_y(\theta)(Y - \mu_y)]^2 \\
&= f'^2_x(\theta)\sigma_X^2 + 2f'_x(\theta)f'_y(\theta)\sigma_{XY} + f'^2_y(\theta)\sigma_Y^2
\end{aligned}$$

Now let $G = f(X, Y) = X/Y$, we can calculate EG and $Var(G)$ as follows:

$$\begin{aligned}
EG &= E(f(X, Y)) \approx f(\mu_x, \mu_y) = \frac{\mu_x}{\mu_y} \\
Var(G) &\approx \frac{1}{\mu_y^2}\sigma_X^2 - 2\frac{\mu_x}{\mu_y^3}\sigma_{XY} + \frac{\mu_x^2}{\mu_y^4}\sigma_Y^2
\end{aligned}$$

Applying the above formulas, we have

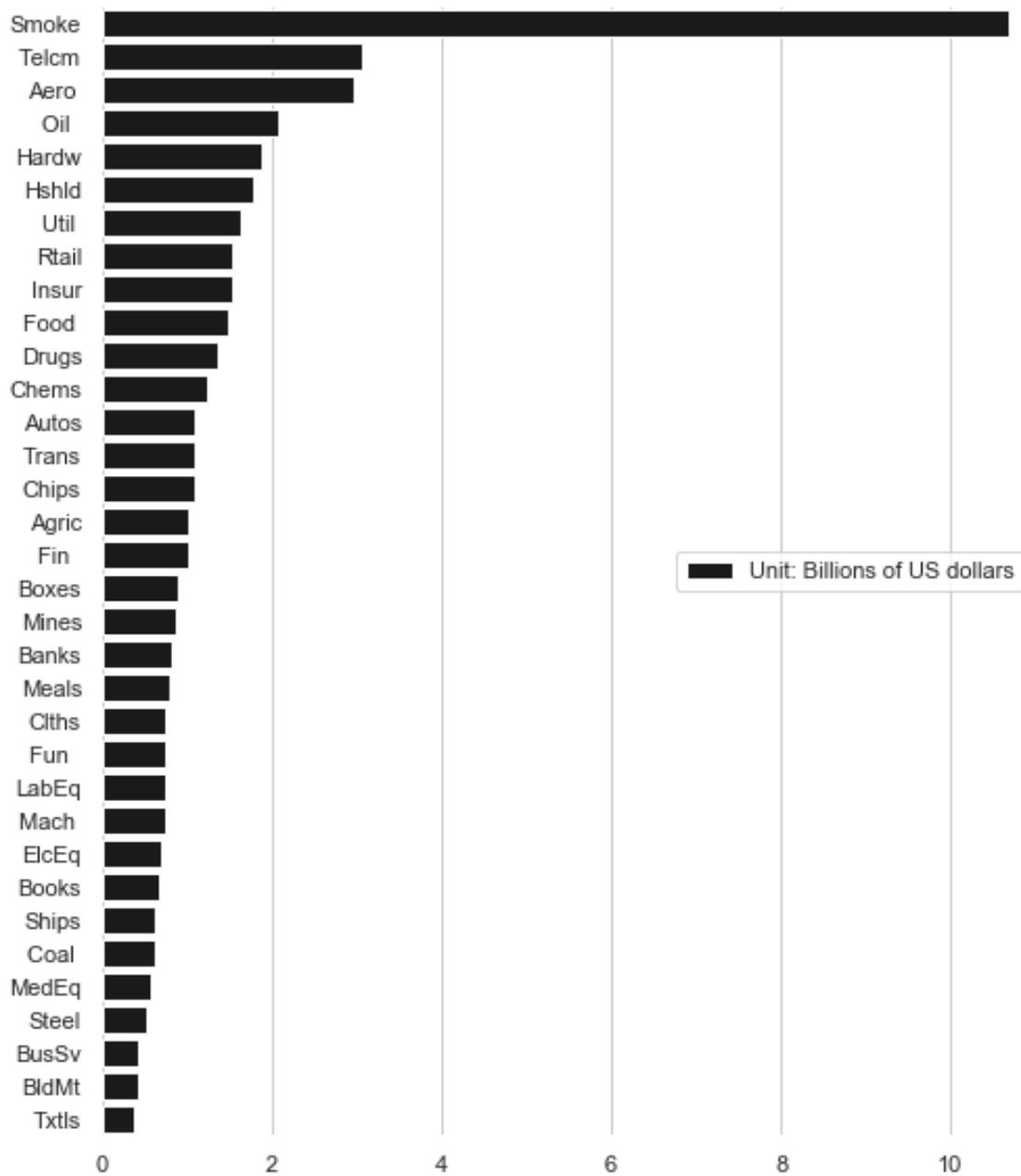
$$Var(b_r^{LR}) = Var\left(\frac{b_r}{1 - \rho\phi}\right) \approx \frac{\sigma^2(b_r)}{(1 - \rho\phi)^2} - \frac{2b_r Cov(b_r, 1 - \rho\phi)}{(1 - \rho\phi)^3} + \frac{b_r^2 \rho^2 \sigma^2(\phi)}{(1 - \rho\phi)^4}$$

where $2Cov(b_r, 1 - \rho\phi) = \sigma^2(b_r) + \rho^2\sigma^2(\phi) - \sigma^2(b_d)$ because $1 - \rho\phi = b_r - b_d$.

A.2 Average firm size across US industries

Figure A.1: Average firm size across US industries

The figure plots the average firm size, measured by the market capitalization, across US industries over the sample period from 1927 to 2018.



A.3 Results of unit root/stationarity tests

Table A.1: Results of unit root/stationarity tests

The table presents the results of unit root/stationarity tests for the variables in the Lintner (1956) modified partial-adjustment model. ***, **, and * indicate rejection of null hypotheses at the 1%, 5%, and 10% significance levels, respectively. The sample period is from 1972 to 2018.

Test	Null Hypothesis	EW		VW	
		ΔD	ΔE	ΔD	ΔE
Aug. Dickey Fuller	Unit Root	-15.94***	-9.47***	-5.43***	-6.77***
DF-GLS	Unit Root	-16.06***	-7.45***	-5.47***	-6.65***
Phillips-Perron	Unit Root	-14.2***	-10.24***	-5.40***	-6.91***
KPSS	Stationarity	0.17*	0.35*	0.23	0.12*
Ng-Perron	Unit Root	-2.39***	-3.36***	-3.28**	-3.30**

B

Appendix to Chapter 3

Figure B.1: Average hedge ratios of commodity indices in portfolio pairs

The figure plots the hedge ratios of commodity indices in pairs with US equity sector, which is averaged across indices over time. The sample period is from January 1991 to December 2019.

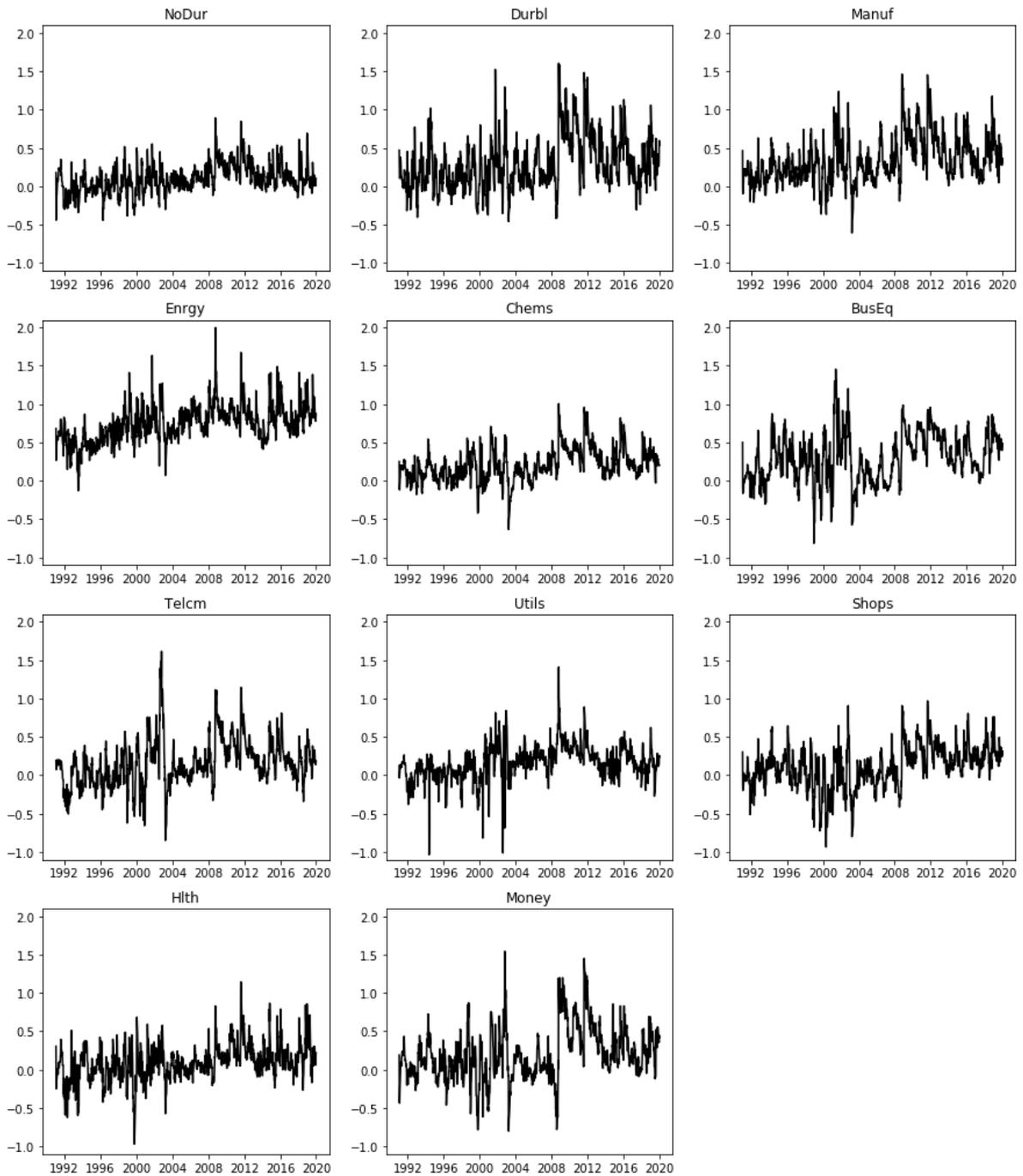
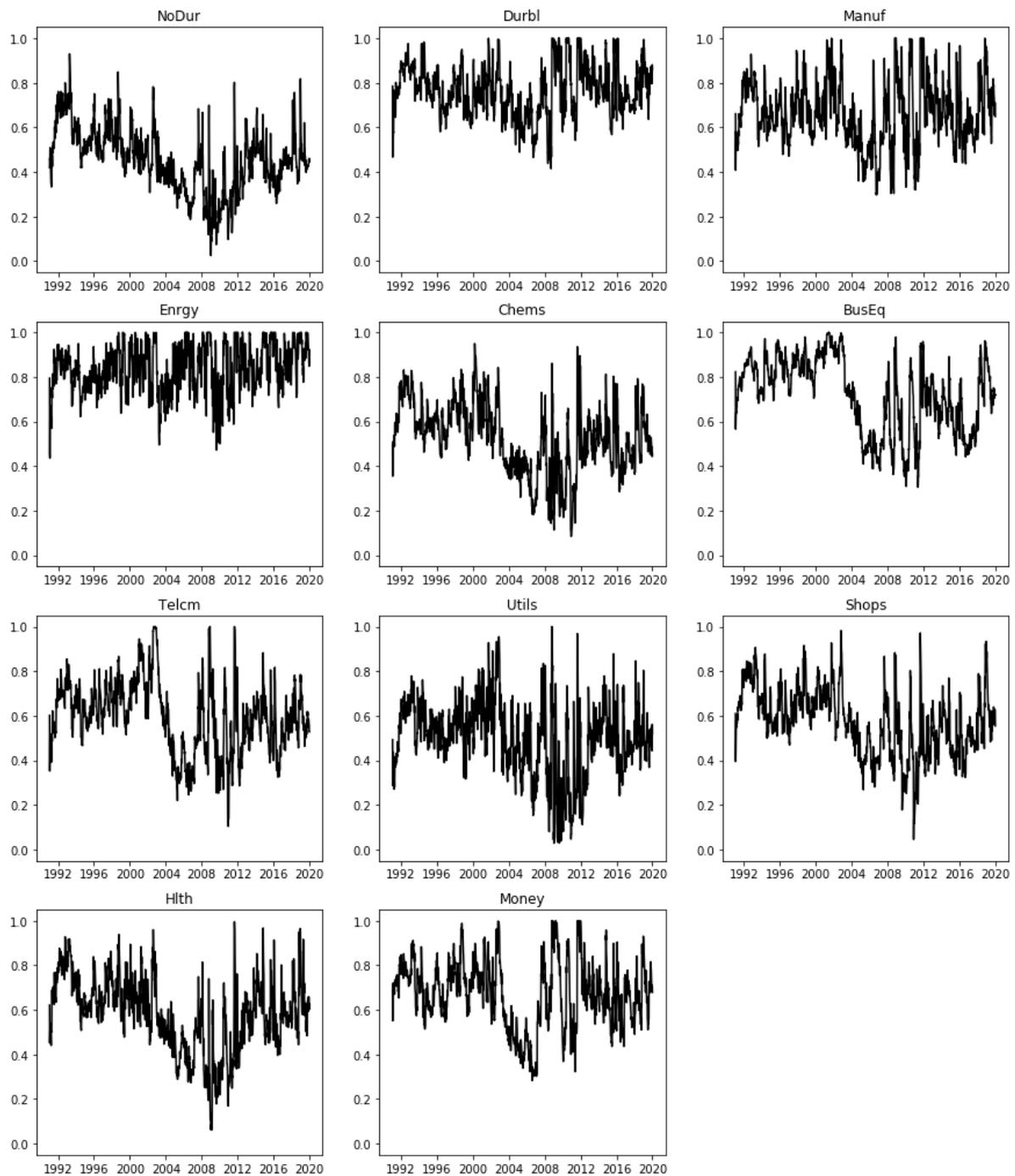


Figure B.2: Average optimal weights of commodity indices in portfolio pairs

The figure plots the optimal weights of commodity indices in pairs with US equity sector, which is averaged across indices over time. The sample period is from January 1991 to December 2019.



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According to §12 part 1 no. 6 of the Doctoral Program Regulations
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I hereby declare, that the

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