Cointegration, Information Transmission, and the Lead-Lag Effect between Industry Portfolios and the Stock Market

Victor Troster[a,*], José Penalva[b,**], Abderrahim Taamouti[c], Dominik Wied[d]

[a] *Universitat de les Illes Balears, Department of Applied Economics, Ctra. Valldemossa, km 7.5, Building: Gaspar Melchor Jovellanos, 07122 Palma de Mallorca, Spain*
[b] *Universidad Carlos III de Madrid, Department of Business, C/ Madrid, 126, 28903 Getafe (Madrid), Spain*
[c] *Durham University Business School, Mill Hill Lane, Durham DH1 3LB, U.K.*
[d] *Institute for Econometrics and Statistics, University of Cologne, Köln, 50923, Germany*

Abstract

This paper shows that lagged information transmission between industry portfolio and market prices entails cointegration. We analyze monthly industry portfolios in the US market for the period 1963-2015. We find cointegration between six industry portfolio and market prices. We show that the equilibrium error, the long-term common factor between industry portfolio and market cumulative returns, has strong predictive power for excess industry portfolio returns. In line with gradual information diffusion across connected industries, the equilibrium error proxies for changes in the investment opportunity set that lead to industry return predictability by informed investors. Forecasting models including the equilibrium error have superior forecasting performance relative to models without it, illustrating the importance of cointegration between the industry portfolio and market prices. Overall, our findings have important implications for investment and risk-management decisions, since the out-of-sample explanatory power of the equilibrium error is economically meaningful for making optimal portfolio allocations.

Keywords: Cointegration, Stock return predictability, Error correction, Information diffusion, Equilibrium error, Out-of-sample forecast

JEL classification: G10; G12; G14; G17

---

*Principal corresponding author. Phone: (+34) 971 17 30 94. Fax: (+34) 971 17 23 89.

**Corresponding author. Phone: (+34) 91 624 96 54. Fax: (+34) 91 624 96 07.

Email addresses: victor.troster@uib.es (Victor Troster), jpenalva@emp.uc3m.es (José Penalva), abderrahim.taamouti@durham.ac.uk (Abderrahim Taamouti), dwied@uni-koeln.de (Dominik Wied)

1. Introduction

This paper shows that lagged information transmission between industry portfolio and market prices entails cointegration. In line with gradual information diffusion across connected industries, the equilibrium-cointegration error proxies for changes in the investment opportunity set that lead to industry return predictability by informed investors. Many studies have investigated the cross-industry return predictability based on the economic links among industries (Hong & Stein, 1999; Hong et al., 2007; Cohen & Frazzini, 2008; Menzly & Ozbas, 2010). Hong et al. (2007) showed that the gradual diffusion of information across industries leads to cross-industry return predictability, examining the ability of lagged industry returns to predict the market return and their interaction with well-known predictors supposed to affect the diffusion of information. Cohen & Frazzini (2008) and Menzly & Ozbas (2010) found that economic links of relationships between customers and suppliers contribute for the cross-industry return predictability. Rapach et al. (2019) showed that past returns of interconnected industries help predict individual industry returns.

In this paper, we investigate the predictability of industry portfolio returns based on a cointegration approach between industry and stock market prices motivated by the economic intuition that some industries, specially those related to basic consumption such as food or retail, will display a stable relationship with the overall economy over time. For these industries, insufficient or excess growth relative to the overall economy will generate economic imbalances that will be reverted over time. In contrast to Hong et al. (2007), who examined the cross-predictability of industry portfolio returns on a short-run basis, we propose a long-run cointegration analysis since investors consider long periods of investment. Granger (1986), Bossaerts (1988), Campbell & Shiller (1988a), and Kanas & Kouretas (2005) have investigated the relation between cointegration and asset prices. These authors found that a vector error-correction model (VECM) obtains more accurate predictions of future asset prices, given that cointegration exists. According to Kasa (1992) and Gallagher (1995), correlation measures between portfolios overlook long-run connections between stock prices. They found that the cointegration analysis improves the predictability of stock prices through a VECM, whereas correlation measures overlook joint stochastic trends between stock markets.

Kanas & Kouretas (2005) found that cointegration between the current price of a portfolio with small firms and a lagged price of a portfolio with large firms is consistent with a lead-lag relationship between prices of portfolios sorted on size. Accordingly, this cointegration relationship provides evidence of a lead-lag effect in returns. Menzly & Ozbas (2010) recommended constructing portfolios according to economic connections between customers and suppliers, by exploring positively correlated fundamentals between industries. Rapach et al. (2019) developed an approach that allows for return predictability across industries, beyond direct customer-supplier links. Our approach extends the analysis of Menzly & Ozbas (2010) and Rapach et al. (2019) to provide an equilibrium error that contributes to the predictability of returns for some industries.

We also analyze the presence of long-term mean reversion to an equilibrium relationship between some industries and the market. Many papers provide evidence of long-term reversals of the stock returns and of mean reversion of stock prices, but only the works of Asness et al. (2000) and Bornholt et al. (2015) investigated whether there are long-term return reversals between US industry portfolios by analyzing the performance of winner-minus-loser strategies. In contrast, we apply an error-correction analysis between cointegrated stock market and industry cumulative returns to check for mean reversion in US industry portfolios.

Our results are consistent with the gradual diffusion of information regarding the long-term relationship between an industry and the market, as in Hong et al. (2007) and Menzly & Ozbas (2010). Uninformed investors, who do not trade using all public information available give rise to long-term mean reversion in industry portfolio returns, which in turn plays an important role on the predictability of industry returns (Fama & French, 1988; Campbell & Shiller, 2005). As a result, the information in the equilibrium error from the cointegrating relationship between an industry and the market has forecasting power for future industry returns.

In our framework, the lagged information transmission between industry portfolio and lagged market returns is a necessary condition for establishing cointegration between the industry portfolio cumulative return (price) and the cumulative market return (price). Following Kanas & Kouretas (2005), if there is a lead-lag effect between industry portfolio and market prices, then we may estimate a common stochastic trend between them by performing a cointegration analysis. If there is no long-run common stochastic trend between them, then cointegration will not arise. Thus, the lagged information transmission is necessary for cointegration by providing a common factor in the regression of the industry portfolio cumulative return on the cumulative market returns.

Our setup has the following testable implications. First, we expect to observe cointegration between the portfolio cumulative return of industries that have an economically meaningful stable long-term relationship with the overall economy and the cumulative return of the market portfolio. Second, as cointegration identifies a long-run relationship between the industry portfolio and the market cumulative return, we can estimate deviations from this relationship, the equilibrium error, as a common factor between industry portfolio and the market cumulative returns.

We find that the equilibrium error, the long-term common factor between industry portfolio and market cumulative returns, has strong predictive power for excess industry portfolio returns. The significantly negative effect of the equilibrium error on future industry returns indicates the presence of long-term reversion in some US industry portfolios to the equilibrium relationship between the cointegrated industries and the overall economy, in consonance with the gradual diffusion of information on this equilibrium relationship. Further, the equilibrium error retains its predictive ability for future excess industry portfolio returns when we include liquidity and risk control variables in the predictive regressions. We corroborate these findings by performing out-of-sample forecasting performance tests.

In addition, we report that the documented predictability helps build portfolios that provide significant premia in comparison with benchmark portfolios. We take the perspective of an investor who uses predictability from a model of time-varying expected returns to sequentially build portfolios. Following Breen et al. (1989) and Pesaran & Timmermann (1995), we assume that investors hold an industry portfolio when the business cycle suggests that industry portfolio returns may outperform bond returns, and otherwise invest in bonds. We also consider a model of time-varying expected returns and volatility. For each period, an investor allocates his wealth between the i-th industry according to an optimal portfolio rule, derived from an extension of Stein's lemma (Johannes et al., 2014). We compare the generated returns with those implied by a model without predictability and with the excess stock market return.

We show that strategies based on time-varying expected returns and volatility generate portfolios with higher Sharpe ratios than a benchmark strategy does. Our results are consistent with Pesaran & Timmermann (1995), Guo (2006), and Johannes et al. (2014), who found economic gains from time-varying trading strategies. Further, our findings are conforming to the results presented in Campbell & Viceira (1999), Barberis (2000), Wachter (2002), and Moreira & Muir (2019), who reported that long-term traders invest more in stocks under mean reversion of the stock returns. Accordingly, long-term investors do not perceive volatility increases as risk increases because of mean-reverting stock returns. The optimal-weighting portfolio strategies using the equilibrium error consider only industry portfolios that revert to their long-run relationship, outperforming buy-and-hold and benchmark strategies. Therefore, we find evidence that investors can use the equilibrium error predictability to improve out-of-sample portfolio performance.

The rest of this paper advances as follows. Section 2 discusses the theoretical framework to develop certain testable conjectures and our data sources. Section 3 reports the main results of forecasting excess industry portfolio returns. Section 4 presents the analysis of trading strategies using the out-of-sample predictability of excess industry portfolio returns from our forecasting models. Finally, Section 5 concludes the paper.

2. Theoretical framework and data

2.1. Theoretical framework

Many papers provide evidence of long-term reversals of stock returns (De Bondt & Thaler, 1985, 1987; Richards, 1997; Malin & Bornholt, 2013) and of mean reversion of stock prices (Fama & French, 1988; Poterba & Summers, 1988; Balvers et al., 2000; Gropp, 2004; Spierdijk et al., 2012), which is the propensity of stock prices to come back to a certain level. According to the efficient market hypothesis (Fama, 1991), the predictability implied by mean reversion should not be observable as stock prices disclose all available information. Thus, mean reversion can be considered as a form of market inefficiency. For example, long-term reversals of stock returns are attributed to the overreaction of investors to financial news (De Bondt & Thaler, 1985, 1987), whereas long-term mean reversion is associated to the irrational pricing of noise investors (Poterba & Summers, 1988) or to rational speculative bubbles (McQueen, 1992).

There are few works that analyzed the presence of long-term reversals in industry portfolio rather than in individual stock returns. Asness et al. (2000) reported long-term reversals in industry portfolio returns of US stock returns calculated on a 60-month formation period. Bornholt et al. (2015) corroborated these findings by using a large range of formation periods (from 36 to 132 months). On the other hand, certain papers investigated whether there are short-term return reversals between industry portfolios. Da et al. (2014) and Hameed & Mian (2015) found no short-term (1-month) reversal effect across industry portfolio returns; both studies documented a short-term momentum across industry portfolios, consistent with Moskowitz & Grinblatt (1999).

This paper considers a model in which there is a stable economic equilibrium relationship between an industry and the overall economy, which is captured by a cointegrating relationship between the industry and the market. For example, consider the long-run relationship between the food industry and the overall economy. An unanticipated positive shock to the economy may include information about future growth in the economy that generates a disproportionate positive effect on the value generated by the food industry, which will gradually be eliminated through the error-correction mechanism as the food industry grows to catch up with growth in the economy as a whole.

In this setting, we consider that information about the long-term relationship between an industry and the market is slowly incorporated into prices, in line with Hong et al. (2007) and Menzly & Ozbas (2010). Thus, mean reversion arises because of uninformed investors in the food industry, who do not invest using all public information available, trading under an inefficient market (Poterba & Summers, 1988). Fama & French (1988) and Campbell & Shiller (2005) assert the importance of long-term mean reversion on stock return predictability. Within this context, the information in the equilibrium error from the cointegrating relationship will have predictive power on industry returns.

In the reference model (i) firms in distinct markets or industries display correlated trends, and (ii) investors specialize in these segments (as in Hong et al., 2007), from which it follows that returns exhibit cross-predictability. Only the investors who specialize in a market may perceive an informative signal from this market, whereas investors who specialize in others markets will ignore this signal. Then, prices incorporate cross-market information signals only partially so that cross-predictability between different market returns arise.

Nevertheless, the empirical analysis of Hong et al. (2007) focuses on short-term forecasts of the market return using lagged industry portfolio returns. In this paper, we interpret the long-run relationship between industry and the market as a "market X" and an industry, like the food industry, as "market Y." In such models, industries are segmented both in terms of investors as well as information. In our case, the segmentation occurs between microeconomic experts and industry-specific investors, and investors who focus only on the macroeconomic relationships and market-wide investments. Such specialization, together with limits to arbitrage between these two groups, generates informational boundaries between markets or industries so that asset returns display cross-predictability.

Within this framework, we identify the predictability of industry portfolio returns from a cointegration analysis between industry and stock market prices (or cumulative returns). Industry portfolios delivers a more accurate analysis of cross-industry predictability. Stocks seldom change their industrial classification, whereas stock prices change over time. Besides, Shleifer & Vishny (1992) state that shocks across industries induce redistributions of industry capital by mergers and acquisitions. Bornholt et al. (2015) assert that the past long-term returns of an industry predict its reversals because the returns of an industry reflect its current state. If investors delay to incorporate information of significant shocks to an industry that may generate a return reversal, then high (low) past long-term returns may be accompanied by low (high) returns in the future. Therefore, the gradual diffusion of information of significant shocks to an industry may generate return reversals and cross-predictability.

Following Kanas & Kouretas (2005), if there is a lead-lag effect between industry portfolio and market prices, then we may estimate a common stochastic trend between them by performing a cointegration analysis. If there is no long-run common stochastic trends between them, then cointegration will not arise. Then, the lagged information transmission is necessary for cointegration by providing a common factor in the regression of the industry portfolio cumulative return on the cumulative market returns. Therefore, the equilibrium error influences stock price changes, specifying the long-run relationship to which stock prices revert.

2.2. Data

Our data consist of monthly returns of the 30 industry portfolios of Kenneth French's website, where each NYSE, AMEX, and NASDAQ stock is assigned to an industry portfolio at the end of June of year t based on its four-digit SIC code at that time. Our sample spans from July 1963 to December 2015. To calculate the market return at time t, $R_{m,t}$, we use the value-weighted return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ at the beginning of month t. We use the one-month US Treasury Bill rate as the risk-free rate at time t, $R_{f,t}$, and we define the excess industry return for the industry i in month t as $R_{i,t} - R_{f,t}$.

Let $R^*_{i,t}$ and $R^*_{m,t}$ be the cumulative industry returns and the cumulative stock market returns, respectively. We use the cumulative 30 industry portfolio returns and the cumulative stock market return as the level variables on which to look for a cointegration relationship. If there is cointegration, then we calculate the equilibrium error from the cointegration relationship between industry portfolio cumulative returns and market cumulative returns, $EE_{i,t}$.

For each industry portfolio return i, we calculate $EE_{i,t}$ as follows. First, we perform an Augmented Dickey-Fuller test (with constant and trend) on the industry portfolio cumulative returns and on the market cumulative returns. If we do not reject the null hypothesis of unit root for the i-th industry cumulative returns and for the stock market cumulative returns at the 5% significance level, then we apply the Johansen (1988, 1995)'s cointegration test between the two cumulative return series. If we cannot reject that there is cointegration at the 5% level, then we calculate $EE_{i,t}$ as the error correction from the VECM between these series. To deal with the multiple testing problem, we apply the Bonferroni-Holm level correction proposed by Holm (1979).

For example, if the i-th industry portfolio cumulative return series and the stock market cumulative returns follow a unit root process, we define the 2×1 vector $\mathbf{y}_t = (R^*_{i,t}, R^*_{m,t})'$ to apply the cointegration test of Johansen (1988, 1995) through a finite-order VECM as follows:

$$\Delta \mathbf{y}_t = \boldsymbol{\alpha}(\boldsymbol{\beta}\mathbf{y}_{t-1} + \boldsymbol{\mu}) + \sum_{j=1}^{p-1} \boldsymbol{\Gamma}_j \Delta \mathbf{y}_{t-j} + \boldsymbol{\gamma} + \boldsymbol{\varepsilon}_t, \tag{1}$$

where $\Delta \mathbf{y}_t \equiv (1 - L)\mathbf{y}_t$, with L as the lag operator, p is the lag order of the VECM, $\boldsymbol{\Gamma}_1, \ldots, \boldsymbol{\Gamma}_{p-1}$ are $2{\times}2$ matrices of parameters, and $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\mu}$, and $\boldsymbol{\gamma}$ are $2{\times}1$ vectors of parameters. We apply the trace test of Johansen (1988, 1995), where the null hypothesis is that the rank of cointegration vectors is 0, $H_0 : rank = 0$. The selected lag order of the VECMs minimizes the Akaike information criteria (AIC) up to a maximum lag of 18 monthly periods. Then, the equilibrium error, $EE_{i,t}$, is the first element of the $2{\times}1$ error-correction vector $\boldsymbol{\beta}\mathbf{y}_{t-1}$ of Equation (1), for each i-th industry cumulative return cointegrated with the market cumulative return. The vector $\boldsymbol{\alpha}$ gives the speed of mean reversion; its elements are negative so that when $EE_{i,t} > 0$ (< 0) the cumulative industry portfolio return is above (below) its long-term equilibrium with the cumulative market return so that $R^*_{i,t}$ is more likely to decrease (increase) and bring the cumulative industry portfolio return back to its equilibrium relationship with the market.

We do not reject the null hypothesis of unit root for all series of industry cumulative returns and for the stock market cumulative return at the 5% level. Therefore, we apply the Johansen (1988, 1995)'s cointegration test between each industry cumulative return and the market cumulative return. Table 1 reports the cointegration test results. We find that six out of 30 industry cumulative returns are cointegrated with the market cumulative return at the 5% significance level (Table 1). To evaluate only the industry cumulative returns that are cointegrated with the stock market cumulative returns, we exclude the remaining 24 industry return portfolios from our analysis throughout the rest of the paper. Thus, we restrict our analysis to the following cumulative industry portfolios that are cointegrated with the cumulative market return: FOOD, BEER, SMOKE, RTAIL, MEALS, and HSHLD. These industries that are cointegrated with the market also fall within the category of industries that have an intuitive long-term relationship with the overall economy.

3. Forecasting excess industry portfolio returns

In this section, we check whether the equilibrium error contributes for forecasting excess industry portfolio returns. We first present in-sample predictive regression results. Next, we evaluate the out-of-sample

Table 1
Johansen cointegration tests.

Industry portfolio	*P*-values	H-B *p*-values	Industry portfolio	*P*-Values	H-B *p*-values
FOOD	.001	**.030**	UTIL	.103	1.000
BEER	.001	**.029**	STEEL	.119	1.000
SMOKE	.001	**.028**	TRANS	.131	1.000
RTAIL	.001	**.027**	SERVS	.154	1.000
MEALS	.001	**.026**	TXTLS	.207	1.000
HSHLD	.002	**.039**	AUTOS	.289	1.000
GAMES	.003	.062	BOOKS	.303	1.000
BUSEQ	.004	.091	OTHER	.320	1.000
CLTHS	.022	.487	MINES	.391	1.000
CHEMS	.029	.616	OIL	.421	1.000
FABPR	.033	.656	WHLSL	.473	1.000
PAPER	.037	.707	CARRY	.535	1.000
CNSTR	.042	.754	HLTH	.551	1.000
TELCM	.047	.803	ELCEQ	.638	1.000
FIN	.098	1.000	COAL	.764	1.000

Note: We perform the cointegration test of Johansen (1988, 1995) between industry cumulative returns and market cumulative returns. The null hypothesis is $H_0 : rank = 0$. The selected lag order of the VECMs minimizes the AIC up to a maximum lag of 18 monthly periods. H-B *p*-values are the *p*-values of the cointegration test adjusted by the Holm-Bonferroni correction proposed by Holm (1979).

predictability of different forecast models for excess industry portfolio returns, to determine whether the equilibrium error displays additional out-of-sample predictability. Finally, we apply tests of out-of-sample forecast performance between nested predictive models.

3.1. In-sample forecast performance

In this subsection, we discuss in-sample forecast results using predictive regression models with the equilibrium error. Inoue & Kilian (2004) showed that in-sample tests have more power than out-of-sample tests, even asymptotically, with no presumption that in-sample tests suffer from greater size distortions than out-of-sample tests do. We perform the following predictive regressions for the excess industry returns:

$$R_{i,t+1} - R_{f,t+1} = \alpha_i + \beta^{EE} EE_{i,t} + \beta x_t + \varepsilon_{i,t+1}, \tag{2}$$

where $R_{i,t+1} - R_{f,t+1}$ is the excess return of industry i on date $t+1$, x_t is another predictor of $R_{i,t+1} - R_{f,t+1}$ observed at date t, $EE_{i,t}$ is the equilibrium error of industry portfolio i on date t, and $\varepsilon_{i,t+1}$ is the resulting residual. We employ t-statistics adjusted by the clustering industry and time effects, as in Petersen (2009)[1]. The predictive regressions of Equation (2) are estimated by pooled ordinary least squares (OLS), which do not suffer from the small-sample bias caused by near-persistent regressors, the Stambaugh bias (Stambaugh, 1999; Hjalmarsson, 2008). Besides, we use a large in-sample period of 605 observations to estimate the predictive regressions of Equation (2). We calculate $EE_{i,t}$ using the full sample. We employ certain relevant predictors of future stock market returns in x_t to consider different reasons for why the equilibrium error may predict future excess industry returns. These predictors are the lagged excess stock market returns ($R_{m,t} - R_{f,t}$), the lagged excess industry portfolio returns ($R_{i,t} - R_{f,t}$), the lagged inflation rate (Fama & Schwert, 1977), and the lagged change in the dividend yield (Campbell & Shiller, 1988b). We choose these variables because they stand for time-varying risk proxies.

We employed the monthly dividends on the Standard & Poor's (S&P) stock price index used in Shiller (2015). We downloaded them from Robert Shiller's website: `http://www.econ.yale.edu/~shiller/data.htm`. Besides, we obtained the US consumer price index to calculate the US inflation rate from the website of the Federal Reserve Bank of St. Louis (`https://fred.stlouisfed.org/`).

There are other possible specifications for the predictive regression of Equation (2), but we want to include only variables that are relevant for out-of-sample predictability in expected industry returns, rather than finding the most general econometric specification for Equation (2). In addition, a more complex model decreases the out-of-sample forecast error bias and increases its variance, which may lead to a lower out-of-sample predictability. Finally, if there is any significant misspecification in our predictive regression (2), it should be displayed in poor out-of-sample predictability of excess industry returns.

Table 2 displays the in-sample regression results of the predictive regression models of Equation (2), with t-statistics adjusted by the clustering industry and time effects in parentheses. We use the standardized variables in the regressions since the variables have different scales, and we scale the estimated coefficients by 100. The small $\bar{R}^2$ values of the predictive regressions are in line with the results presented in Lettau & Ludvigson (2001), Campbell & Thompson (2008), and Welch & Goyal (2008), among others; predictive regressions are expected to have a small explanatory power because narrow R^2 values may provide great profits for investors. We verify this issue on Section 4.

Rows (2)-(4) of Table 2 show that the lagged excess industry portfolio returns, the lagged inflation rate, and the lagged change in the dividend yield help predict excess industry returns, as their estimated

[1]We thank Mitchell A. Petersen for the Stata program, which can be downloaded from: `http://www.kellogg.northwestern.edu/faculty/petersen/htm/papers/se/se_programming.htm`

coefficients are statistically significant. The lagged excess market returns are, however, not statistically significant for future excess industry returns at the 5% level (row (1) of Table 2). Row (5) indicates that the equilibrium error helps predict excess industry returns. The common factor between the industry portfolio and the stock market cumulative returns has correlated fundamentals with excess industry returns as the estimated coefficient of $EE_{i,t}$ is statistically significant. Besides, the estimated coefficient is negative, indicating an error-correction mechanism of the equilibrium error to future excess industry returns, in line with our theoretical framework outlined in Subsection 2.1. Consistent with lagged information transmission between the market and industries, prices partially incorporate cross-market information signals so that the error-correction mechanism occurs gradually over time and equilibrium errors help predict future price movements. The negative sign of the equilibrium error provides evidence of reversion of industry portfolio returns to their long-term relationship with the market portfolio.

Rows (6)-(9) highlight that the equilibrium error remains significant when we add the lagged excess market returns, excess industry returns, inflation rate, and dividend yield change. Thus, the equilibrium error retains its predictive ability for future excess industry portfolio returns when we include liquidity and risk control variables in the predictive regression of Equation (2).

3.2. Out-of-sample forecast performance

In this subsection, we evaluate the out-of-sample forecasting performance of the proposed forecast models. Bossaerts & Hillion (1999), Goyal & Welch (2003), and Welch & Goyal (2008), among others, question the in-sample evidence of stock return predictability, as they showed that even the best forecast models lack out-of-sample forecasting power. Based on the results of Table 2, we evaluate the out-of-sample predictability of four forecast models: (i) a model including the lagged excess industry returns, $R_{i,t} - R_{f,t}$; (ii) an augmented model including $R_{i,t} - R_{f,t}$ and $EE_{i,t}$; (iii) a model that includes only $EE_{i,t}$; and (iv) a benchmark model of the historical average excess return estimated through period t, $\bar{R}_{i,t} - \bar{R}_{f,t}$.

We perform two analyses. First, we assume that investors know the cointegration parameters that generate $EE_{i,t}$, where $EE_{i,t}$ is estimated using all the observations of the sample. This setup conforms to models of agents with rational expectations, who are fully informed about the whole economy. In the second analysis, the cointegration parameters are estimated recursively using only information available at the time of the forecast. This analysis is more realistic and has more applicability because investors can use only the data available at the time of the forecast to make decisions.

Table 2
In-sample forecasting excess industry returns, $R_{i,t+1} - R_{f,t+1}$.

	$R_{m,t} - R_{f,t}$	$R_{i,t} - R_{f,t}$	INF_t	DY_t	$EE_{i,t}$	$\bar{R}^2$
(1)	6.268					.004
	(1.563)					
(2)		9.399**				.009
		(2.263)				
(3)			-6.414*			.004
			(-1.675)			
(4)				-4.943*		.002
				(-1.873)		
(5)					-2.201**	.002
					(-2.266)	
(6)	6.286				-2.201**	.004
	(1.549)				(-2.154)	
(7)		9.452**			-2.091*	.009
		(2.291)			(-1.923)	
(8)			-6.330*		-1.928**	.004
			(-1.778)		(-2.132)	
(9)				-4.898*	-2.169**	.002
				(-1.838)	(-2.255)	

Note: This table displays in-sample forecasts using the predictive regression (2) for the one-month-ahead excess industry portfolio returns, $R_{i,t+1} - R_{f,t+1}$, on some variables. The t-statistics adjusted by the clustering industry and time effects are reported in parentheses, where * and ** denote significance at the 10% and 5% levels, respectively. $R_{m,t} - R_{f,t}$ is the lagged excess market return. $R_{i,t} - R_{f,t}$ is the lagged excess industry portfolio return. INF_t is the lagged CPI inflation rate. DY_t is the lagged change in the dividend yield of the market portfolio. The equilibrium error, $EE_{i,t}$, is the error from the cointegration relationship between the i-th industry cumulative return and the market cumulative return. We estimate $EE_{i,t}$ recursively. $\bar{R}^2$ is the adjusted-R^2. All the variables are standardized, and the estimated coefficients are scaled by 100.

3.2.1. Fixed equilibrium error

Table 3 reports the out-of-sample performance of the proposed forecasting models. We calculate four forecast performance statistics: (i) the root mean squared error (RMSE), (ii) the differences in mean squared errors (MSE) between a forecasting model and the historical average benchmark model, (iii) the Theil's U inequality coefficient (U), and (iv) the out-of-sample R^2 statistic (R^2_{OS}), which is calculated as follows:

$$R^2_{OS} = 1 - \frac{\sum_{t=T+1}^{T+h}(r_t - \hat{r}_t)^2}{\sum_{t=T+1}^{T+h}(r_t - \bar{r}_t)^2}, \tag{3}$$

where $r_t = R_{i,t} - R_{f,t}$ is the excess industry portfolio return, $\hat{r}_t$ is the predicted value from a predictive regression estimated through period T, $\bar{r}_t$ is the historical average of the excess industry return estimated through period T, h is the number of out-of-sample periods, and T is the sample size. We use a large in-sample period to calculate the equilibrium error ($EE_{i,t}$) because it is a long-term common factor between the industry portfolio and stock market cumulative returns. We employ two thirds of the sample for estimation (361 months) and leave one third of the sample for performing out-of-sample forecasts. In the out-of-sample forecasts, we first run an in-sample regression using data from Jul.1963 through Jul.1995 and perform a forecast of the excess industry returns for Aug.1995. After computing the forecast, we increase the in-sample period to Aug.1995 and perform a forecast for Sep.1995. We repeat this recursive out-of-sample procedure for each monthly forecast.

We apply the MSPE-adjusted (Mean Squared Prediction Error-adjusted) test of Clark & West (2007) to compare the RMSE of the first three models with that of the historical average model. Under the null hypothesis there is no difference between the MSE (implied by the RMSE) of the historical average model and that of the alternative model. Under the alternative hypothesis, the alternative model has a smaller MSE. Besides, we apply a block bootstrap of Künsch (1989) on $R_{i,t} - R_{f,t}$, $t = 1, \ldots, T$, to calculate a test of differences for the out-of-sample R^2 statistic (R^2_{OS}) and the Theil's U inequality coefficient. We first generate 1000 block-bootstrap samples of $R_{i,t} - R_{f,t}$ using a block size of 5. Then, we compute the forecast errors and the forecast performance statistics for each bootstrap sample, which allows us to calculate the bootstrap standard deviation of R^2_{OS} and U across the block-bootstrap samples. We use a block of size 5 following Künsch (1989), who suggested using a block b that satisfies $b < CT^{1/3}$, for a constant $C > 0$. The bootstrap p-value is the mean of the number of times that the block-bootstrap statistic exceeds the statistic calculated using the original sample.

We compare the R^2_{OS} statistics of the model including the lagged excess industry returns ($R_{i,t} - R_{f,t}$) and of the augmented model with $EE_{i,t}$ ($R_{i,t} - R_{f,t}$ & $EE_{i,t}$) with that of the model including only $EE_{i,t}$. We test whether the U statistic of the historical average model is different from that of the other three models, since the historical average is our benchmark model. Under the null hypothesis, there is no difference between the performance statistics, whereas this difference is significantly different from zero under the alternative hypothesis.

Panel A of Table 3 shows that the model including the lagged excess industry returns ($R_{i,t} - R_{f,t}$) and the model including only $EE_{i,t}$ have the lowest RMSE among the four models over the period Aug.1995-Dec.2015. Nevertheless, the RMSE statistics of these models are not significantly different from that of the benchmark model. The model including the lagged excess returns has the lowest U and the highest R^2_{OS} statistics among all models, although they are not statistically different from the R^2_{OS} statistic of the model including only $EE_{i,t}$ and from the U statistic of the benchmark model. Panel B of Table 3 displays the out-of-sample results for the subsample period Sep.2005-Dec.2015. In line with the full-sample results, the model including only $EE_{i,t}$ has the lowest RMSE together with the highest R^2_{OS} among all models. In addition, the R^2_{OS} of the model with only $EE_{i,t}$ is statistically different from that of the other models.

Table 3
Out-of-sample forecasting: Fixed equilibrium error.

	$R_{i,t} - R_{f,t}$ (1)	$R_{i,t} - R_{f,t}$ & $EE_{i,t}$ (2)	$EE_{i,t}$ (3)	Historical average (4)
		A. Aug.1995-Dec.2015		
RMSE	.0509	.0510	.0509	.0510
Diff. in MSE	-.0013	.0004	-.0006	
C&W p-value	(0.100)	(0.165)	(0.178)	
U	.9939	.9972	.9954	.9965
U bootstrap p-value	(0.738)	(0.954)	(0.829)	
R^2_{OS}	.0051	-.0015	.0022	-
R^2_{OS} bootstrap p-value	(0.434)	(0.270)		
		B. Sep.2005-Dec.2015		
RMSE	.0410	.0410	.0408	.0408
Diff. in MSE	.0017	.0017	.0000	
C&W p-value	(0.286)	(0.311)	(0.237)	
U	.9875	.9874	.9825	.9824
U bootstrap p-value	(0.332)	(0.328)	(0.985)	
R^2_{OS}	-.0104	-.0103	-.0002	-
R^2_{OS} bootstrap p-value	(0.016)	(0.012)		

Note: This table displays four out-of-sample forecast performance statistics: (i) the root mean squared error (RMSE), (ii) the differences (scaled by 100) in mean squared errors (MSE) between a forecasting model and the benchmark model (4), (iii) the Theil's U inequality coefficient (U), and (iv) the out-of-sample R^2 statistic (R^2_{OS}) of Eq. (3). We apply a forecast model including the lagged excess industry returns $R_{i,t} - R_{f,t}$, an augmented model with $R_{i,t} - R_{f,t}$ and $EE_{i,t}$, a model including only the equilibrium error $EE_{i,t}$, and an historical average model estimated through period t, $\bar{R}_{i,t} - \bar{R}_{f,t}$, to forecast the excess industry returns. The equilibrium error ($EE_{i,t}$) is the error from the cointegration relationship between the i-th industry cumulative return and the stock market cumulative return. We estimate the $EE_{i,t}$ using the full sample. C&W p-value is the p-value of the MSPE-adjusted test of Clark & West (2007) that compares the MSE of the first three models with that of the historical average model (4). Under the null hypothesis, there is no difference between the MSE (implied by the RMSE) of the model (4) and that of the alternative model, against the alternative hypothesis that the augmented model has a smaller MSE. Bootstrap p-value is the block-bootstrap p-value of the test of differences for the out-of-sample R^2 statistic (R^2_{OS}) and the Theil's U inequality coefficient. We compare the R^2_{OS} statistics of the models (1) and (2) with that of (3), whereas we compare the U statistic of (4) with that of the other three models. Under the null hypothesis, there is no difference between the performance statistics, whereas this difference is significantly different from zero under the alternative hypothesis. We use 1000 bootstrap samples with a block length of 5 to calculate the bootstrap p-values.

For robustness, Figure 1 plots the recursive RMSE ratio of the model including only $EE_{i,t}$ (col. (3) of Table 3) to the benchmark model (col. (4) of Table 3) and to a model including only the lagged excess industry returns $R_{i,t} - R_{f,t}$ (col. (1) of Table 3) over time. The horizontal axis indicates the initial forecast date. For instance, the RMSE ratio of Aug.1995 corresponds to the forecast period Aug.1995-Dec.2015, where Aug.1995 is the initial forecast date. We employ an in-sample period of at least 361 months (two thirds of the sample). The initial forecast date ranges from Aug.1995 to Aug.2005. Figure 1 shows that both two ratios are smaller than one for most of the initial forecast dates, indicating that the model including only $EE_{i,t}$ outperforms the historical average model and the model including only $R_{i,t} - R_{f,t}$.

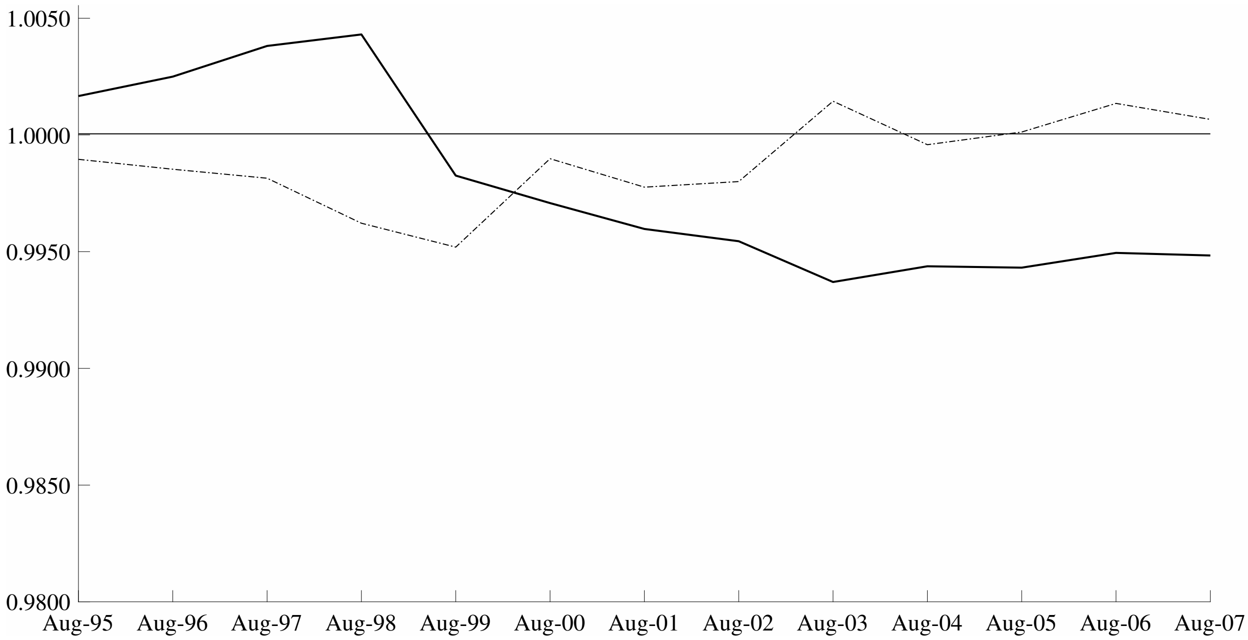

Fig. 1. RMSE ratio of the model including only $EE_{i,t}$ to the model with $R_{i,t} - R_{f,t}$ (solid line) and to the historical average model (dashed line): Fixed equilibrium error.

Overall, Table 2 shows that the equilibrium error is an important factor in determining future returns, and it has the expected economic effect: it drives differences between a key set of industries towards their long-term relationship with the overall economy. Table 3, however, indicates that the fixed equilibrium error (and the lagged excess return) are not significantly better predictors than the historical average. Nevertheless, our analysis covers long time periods with significant changes in the structure of the economy, which may have altered the parameters of the hypothesized long-term relationship between industries and the market.

3.2.2. Recursively estimated equilibrium error

To address possible changes in the structural relationship between industries and the market, we estimate the model dynamically, using only historical information. For each one of the cointegrated industries, we estimate the parameters of the error-correction model each month using the data available up to that month, and we compute the equilibrium error for that month. We call this estimate as the recursive equilibrium error. We first calculate the equilibrium error from the cointegration relationship between industry portfolio and market cumulative returns using data from Jul.1963 through Jul.1995. Then, we run an in-sample regression using data from Jul.1963 through Jul.1995 and we make a forecast for the excess industry returns for Aug.1995. After computing the forecast, we update the sample to Aug.1995 to recalculate $EE_{i,t}$ and make a forecast for Sep.1995 and so forth. We now apply the same analysis as in Table 3.

Table 4 displays the out-of-sample performance of the proposed forecast models using recursively estimated $EE_{i,t}$ in the augmented model and in the model including only $EE_{i,t}$. The model that includes only $EE_{i,t}$ has the lowest RMSE among all models, outperforming the benchmark model at the 10% significance level as indicated by the MSPE-adjusted test of Clark & West (2007). The model including only $EE_{i,t}$ also has the lowest U and the highest R^2_{OS} statistics among all models, but they are not statistically different from that of the other models. These results are robust for the subsample period Sep.2005-Dec.2015; the model that includes only $EE_{i,t}$ outperforms the other models in all criteria (Panel B of Table 4), and the R^2_{OS} of the model with only $EE_{i,t}$ is statistically greater than that of the other models.

Figure 2 plots the recursive RMSE ratio of the model including only $EE_{i,t}$ (col. (3) of Table 4) to the historical average model (col. (4) of Table 4) and to the model including only $R_{i,t} - R_{f,t}$ (col. (1) of Table 4) over time. The horizontal axis indicates the initial forecast date. Consistent with the results displayed in Figure 1, Figure 2 shows that the model including only $EE_{i,t}$ outperforms the other two models for different initial forecast dates. Overall, these findings indicate that the dynamic recursively estimated equilibrium error enhances the out-of-sample predictability of excess industry returns relative to the historical benchmark model.

3.3. Testing out-of-sample forecast performance

In this subsection, we include additional tests of the out-of-sample forecast performance between nested predictive models using different sampling periods as an additional way to deal with possible changes in the equilibrium relationship between the industries and the market. We apply the mean squared forecasting error (MSE) ratio between two forecast models, the encompassing test (ENC-NEW) of Clark & McCracken (2001), the MSPE-adjusted test (C&W) of Clark & West (2007), and the MSE-F test of McCracken (2007). The ENC-NEW and the C&W test whether the benchmark model encompasses all the relevant information about future excess industry returns, against the alternative hypothesis that the augmented model provides

Table 4
Out-of-sample forecasting: Recursively estimated equilibrium error.

	$R_{i,t} - R_{f,t}$ (1)	$R_{i,t} - R_{f,t}$ & $EE_{i,t}$ (2)	$EE_{i,t}$ (3)	Historical average (4)
		A. Aug.1995-Dec.2015		
RMSE	.0509	.0509	.0508	.0510
Diff. in MSE	-.0013	-.0014	-.0025	
C&W p-value	(0.100)	(0.101)	(0.072)	
U	.9939	.9937	.9917	.9965
U bootstrap p-value	(0.761)	(0.610)	(0.186)	
R^2_{OS}	.0051	.0055	.0095	-
R^2_{OS} bootstrap p-value	(0.491)	(0.239)		
		B. Sep.2005-Dec.2015		
RMSE	.0410	.0410	.0408	.0408
Diff. in MSE	.0017	.0012	-.0004	
C&W p-value	(0.286)	(0.273)	(0.196)	
U	.9875	.9860	.9813	.9824
U bootstrap p-value	(0.347)	(0.496)	(0.760)	
R^2_{OS}	-.0104	-.0074	.0022	-
R^2_{OS} bootstrap p-value	(0.094)	(0.032)		

Note: This table displays four out-of-sample forecast performance statistics with the same specifications of Table 3, except that $EE_{i,t}$ is recursively estimated using only data available at the time of forecast. C&W p-value is the p-value of the MSPE-adjusted test of Clark & West (2007) that compares the MSE of the first three models with that of the historical average model (4). Under the null hypothesis, there is no difference between the MSE (implied by the RMSE) of the model (4) and that of the alternative model, against the alternative hypothesis that the augmented model has a smaller MSE. Bootstrap p-value is the block-bootstrap p-value of the test of differences for the out-of-sample R^2 statistic (R^2_{OS}) and the Theil's U inequality coefficient. We compare the R^2_{OS} statistics of the models (1) and (2) with that of (3), whereas we compare the U statistic of (4) with that of the other three models. Under the null hypothesis, there is no difference between the performance statistics, whereas this difference is significantly different from zero under the alternative hypothesis. We use 1000 bootstrap samples with a block length of 5 to calculate the bootstrap p-values.

additional information. The MSE-F checks whether the mean-squared forecasting error of the augmented model is significantly smaller than that of the benchmark model.

We perform these tests using the historical average model as a benchmark model. We continue to use the recursively estimated $EE_{i,t}$ using only observations up to the forecast date. To compute the additional ENC-NEW and MSE-F statistics with their critical values (as derived by Clark & McCracken (2001) and by McCracken (2007), respectively) we need to fix a new insample period. We select in-sample periods of 227 and 303 observations that imply ratios of out-of-sample to in-sample observations (π) of 0.6 and 1.0, respectively. The initial forecast months are January 1997 for $\pi = 0.6$ and September 1990 for $\pi = 1.0$. We recursively update the sample to make the forecast for the next month.

Table 5 reports the results of the out-of-sample forecast performance tests. Rows (3) and (6) of Table

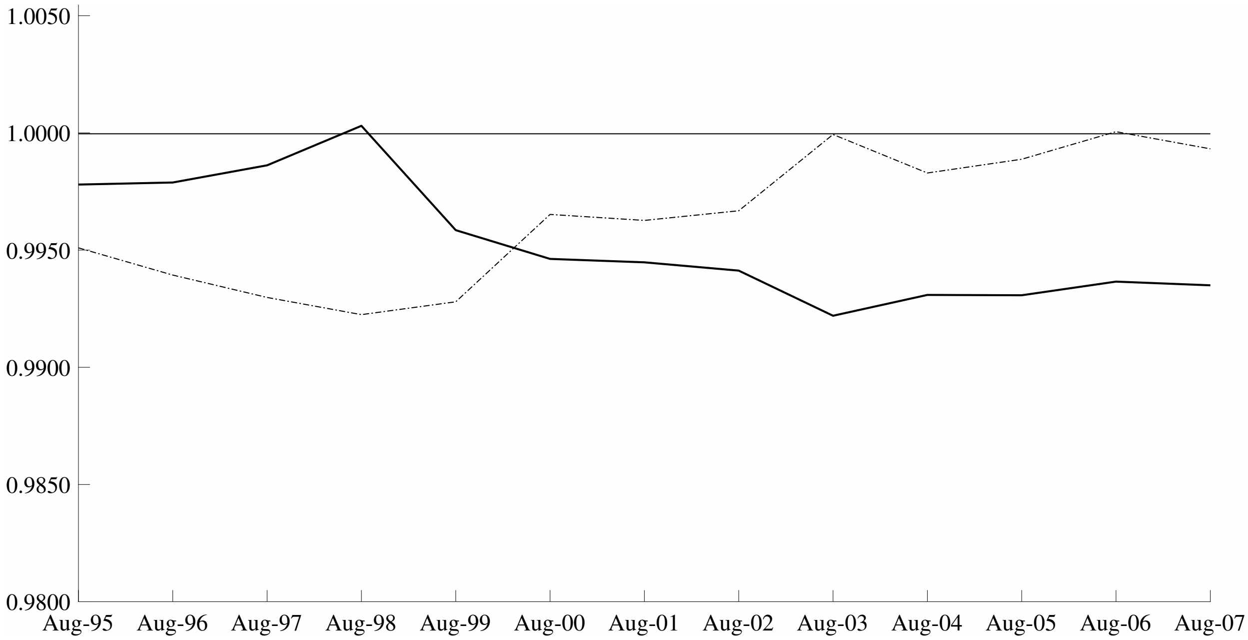

Fig. 2. RMSE ratio of the model including only $EE_{i,t}$ to the model with $R_{i,t} - R_{f,t}$ (solid line) and to the historical average model (dashed line): Recursively estimated equilibrium error.

5 show that the model including only $EE_{i,t}$ has a smaller MSE than that of the benchmark model since the MSE ratio of the model with $EE_{i,t}$ to the benchmark model is smaller than one. Consistent with the MSE ratio, the MSE-F test rejects the null hypothesis that the benchmark model has a MSE equal to that of the model including only $EE_{i,t}$ at the 5% significance level. Moreover, the ENC-NEW test results indicate that the model including only $EE_{i,t}$ outperforms the historical average model at the 5% significance level. The C&W test also provides evidence that the model including only $EE_{i,t}$ outperforms the benchmark model at the 10% level, in line with the results presented in Table 4. These findings are robust for different ratios of out-of-sample to in-sample observations used in the forecast models. Rows (1)-(2) of Table 4 illustrate that the model including the lagged excess industry returns $R_{i,t} - R_{f,t}$ and the augmented model including $EE_{i,t}$ significantly outperform the historical average model at the 5% level for $\pi = 0.6$. Nevertheless, these two models do not outperform the benchmark model for $\pi = 1.0$ at the 5% level according to the MSE-F and C&W test results presented in Rows (4)-(5).

In sum, Table 5 documents that the model including only $EE_{i,t}$ has additional forecasting power for future excess industry returns, and it confirms that there exists a long-term relationship between the selected industries and the market, that deviations from this relationship have predictive power on future returns in an economically meaningful way, and that this relationship is dynamic.

Table 5
Out-of-sample forecast performance tests.

Models	$\frac{MSE_A}{MSE_B}$	ENC-NEW Statistic	ENC-NEW Asy. CV	MSE-F Statistic	MSE-F Asy. CV	C&W Statistic	C&W *P*-value
			$\pi = 0.6$				
(1) $R_{i,t} - R_{f,t}$ vs. historical average	.992	4.111**	1.584	1.904**	1.554	1.342*	0.090
(2) $R_{i,t} - R_{f,t}$ & $EE_{i,t}$ vs. historical average	.991	4.037**	2.234	1.997**	1.891	1.332*	0.091
(3) $EE_{i,t}$ vs. historical average	.988	3.087**	1.584	2.770**	1.554	1.536*	0.062
			$\pi = 1.0$				
(4) $R_{i,t} - R_{f,t}$ vs. historical average	1.002	4.338**	1.584	-0.606	1.548	1.211	0.113
(5) $R_{i,t} - R_{f,t}$ & $EE_{i,t}$ vs. historical average	1.002	4.222**	2.234	-0.643	1.802	1.192	0.117
(6) $EE_{i,t}$ vs. historical average	.993	3.817**	1.584	2.249**	1.548	1.556*	0.060

Note: This table presents the mean-squared forecasting error ratio of the augmented model to the benchmark model (MSE_A/MSE_B), the encompassing test (ENC-NEW) of Clark & McCracken (2001), the MSE-F test of McCracken (2007), and the MSPE-adjusted test (C&W) of Clark & West (2007). The ratio π is the proportion of out-of-sample to in-sample observations. The benchmark model used for these tests is the historical average model. We compare the benchmark model with a model including the lagged excess industry returns $R_{i,t} - R_{f,t}$, an augmented model with $R_{i,t} - R_{f,t}$ and $EE_{i,t}$, and a model including only the equilibrium error $EE_{i,t}$. The ENC-NEW and the C&W test whether the benchmark model encompasses all the relevant information about future excess industry returns, against the alternative hypothesis that the augmented model including $EE_{i,t}$ provides additional information. The MSE-F checks whether the benchmark model has a smaller mean-squared forecasting error than that of the augmented model including $EE_{i,t}$. $EE_{i,t}$ is recursively estimated using only data available at the time of forecast. Columns 4 and 6 report the asymptotic 95% critical values (Asy. CV) provided by Clark & McCracken (2001) and McCracken (2007), respectively. The notation * and ** denote rejection of the null hypothesis at the 10% and 5% significance levels, respectively.

4. Economic significance of forecasting

In this section, we verify whether the out-of-sample predictability of the equilibrium error allows investors to obtain returns with higher Sharpe ratios than that of a benchmark strategy. For this purpose, we consider two widely used market timing strategies. Following Breen et al. (1989) and Pesaran & Timmermann (1995), we employ a strategy where investors hold an industry portfolio if the predicted excess industry portfolio return is positive and hold bonds otherwise. Next, we analyze a investment strategy used by Kandel & Stambaugh (1996), Stambaugh (1999), and Johannes et al. (2014), in which investors choose between industry portfolios and bonds based on a static capital asset pricing model (CAPM). We report only the results using the recursively estimated equilibrium error in both analyses, which are more realistic for investors.

4.1. Switching portfolio strategies

We first consider switching portfolio strategies, which have been widely used in the literature (see Breen et al., 1989; Pesaran & Timmermann, 1995; Guo, 2006). According to these strategies, investors hold an industry portfolio in periods in which the business cycle suggests that industry portfolio returns are going to outperform bond returns (i.e., when the predicted excess industry return is positive), and they hold bonds otherwise.

We describe the switching portfolio strategy as follows. We first estimate a forecast model for excess industry returns as in Equation (2) from the beginning of the sample up to time t, and we use the parameter estimates to forecast the excess return for each industry portfolio at time $t+1$. Then, we choose the industry portfolios with positive expected excess returns and hold them during the following period. We build an equal-weighted industry portfolio with positive excess returns. If no expected excess industry return is higher than zero at $t+1$, then we hold a bond during the following period. We update our sample period by including the observations at $t+1$, and re-estimate Equation (2) from the beginning of the sample period up to $t+1$. We use the parameter estimates to forecast the excess return for each industry portfolio in the period $t+2$. Next, we select the industry portfolios with positive expected excess returns on this period and hold them during the following period. We repeat this process for all sample periods. Based on our forecast results, we propose three specifications for Equation (2): a model using the lagged excess industry returns, an augmented model with the lagged equilibrium error, and a model including only the lagged equilibrium error. We denote the resulting portfolio as the switching portfolio (SP).

For comparison purposes, we calculate the returns obtained from the historical average portfolio and from a buy-and-hold strategy. In the historical average portfolio strategy, we generate a portfolio based on the historical average excess returns. We apply the same procedure as in the SP strategy so that we use the historical average excess returns, from the beginning of the sample up to time t, to forecast the excess return of each industry portfolio. We hold the market portfolio in the buy-and-hold strategy. Our cointegration analysis implies two trading-strategy components. The first one is a selection component as we perform our strategy only on industry portfolios whose cumulative returns are cointegrated with the market cumulative returns. The second one is a variable component that is the equilibrium error since it has out-of-sample predictability for excess industry returns.

4.2. Optimal portfolio weighting strategies

In this subsection, we describe the optimal portfolio weighting strategy, adopted by Kandel & Stambaugh (1996), Stambaugh (1999), Pástor & Stambaugh (2000), Pástor (2000), and Johannes et al. (2014). This strategy includes information on the magnitude of the forecast excess industry return normalized by its forecast conditional variance, whereas the switching portfolio strategy just gives information on the signs of the predicted excess industry returns. Liu (2007), Egloff et al. (2010), Zhou & Zhu (2012), and Moreira & Muir (2017), among others, demonstrate that it is important to consider changes in the volatility of the returns for deriving optimal portfolio strategies. For instance, Moreira & Muir (2019) document that long-term portfolio strategies that neglect fluctuations in volatility lose about 2% of the wealth per year. As a result, the optimal portfolio weighting strategy is more reliable and precise than the switching portfolio strategy. The optimal portfolio weighting strategy assumes that investors solve a single-period optimal portfolio problem as follows:

$$\max_{\omega_t} E\left[U(W_{t+1})|R^t\right] := \max_{\omega_t} \int U(W_{t+1})\,\Pr(R_{t+1}|R^t)dR_{t+1},$$

where R^t is a vector of observed compounded returns up to time t, $W_{t+1} = W_t[\omega_t R_{i,t} + (1-\omega_t)R_{f,t}]$ is the wealth of the investors at $t+1$, ω_t is the weight of the total wealth allocated in stocks at time t ($\omega_t \in [0,1]$), $\Pr(R_{t+1}|R^t)$ is the predictive distribution of future returns, and the maximization of the investors' utility function is subject to the usual budget constraint. We assume that the investors' utility function, $U(W_{t+1})$, is strictly increasing, twice differentiable, and concave in the portfolio weight (ω_t). By solving for the single-period optimal portfolio, investors optimally allocate a fraction of the total wealth in stocks (ω_t) as follows:

$$\omega_t = \frac{1}{\gamma}\frac{E\left[R_{i,t+1} - R_{f,t+1}|R^t\right]}{E\left[\sigma^2_{i,t+1}|R^t\right]}, \tag{4}$$

and a fraction in bonds ($1-\omega_t$), where γ denotes the investors' coefficient of relative risk aversion, $E[R_{i,t+1} - R_{f,t+1}|R^t]$ is the forecast excess industry return, and $E[\sigma^2_{i,t+1}|R^t]$ is the forecast conditional variance obtained from an AR(2) model of the realized variance, $\sigma^2_{i,t}$. For comparison purposes, we consider the three forecast models discussed earlier to predict the excess industry returns.

We describe the optimal weighting portfolio strategy as follows. We estimate a predictive regression in Equation (2) using data from the beginning of the sample up to time t, and we use the parameter estimates to forecast the excess return for each industry portfolio at time $t + 1$. We update the sample period with the observations at $t + 1$, re-estimate the predictive regression and forecast the expected excess returns for $t + 2$ and so forth. Then, given a forecast, we invest the optimal fraction of total wealth of Equation (4) in an industry portfolio at time t if $\omega_t > 0$ for this portfolio. We denote the resulting portfolio as the optimal-weighting portfolio (OWP).

As in the SP strategy, we propose three forecast models for excess industry returns as in Equation (2): a model using the lagged excess industry returns, an augmented model with the lagged equilibrium error, and a model including only the lagged equilibrium error. We also use the historical average excess returns, from the beginning of the sample up to time t, to forecast the excess returns of each industry portfolio. We focus on the single-period optimal allocation portfolio problem. For simplicity, we ignore the estimation uncertainty, short-selling of assets, or borrowing from bond markets, i.e. $\omega_t \in [0, 1]$. We assume that the coefficient of relative risk aversion of the investors' utility function, γ, is $\gamma = 5$ in the calculation of the optimal weights in Equation (4). Unreported results show, however, that our findings are robust to alternative values of γ.

4.3. Results

Table 6 reports the mean, the standard deviation (S.D.), and the Sharpe ratio (S.R.) of the annualized returns on portfolios based on the switching portfolio and optimal-weighting portfolio strategies. The Sharpe ratio of the OWP based on a predictive regression including only the equilibrium error, OWP-$EE_{i,t}$, is the highest among all possible strategies. Therefore, both the selection and variable components implied by our cointegration analysis improve the portfolio performance.

We find similar results for the other subsample periods presented in Panels B-C of Table 6. For instance, the OWP strategy based on the model with $EE_{i,t}$ has a Sharpe ratio of 74.6% compared with 46.5% for the OWP strategy based on the historical average returns over the period Aug.1995-Aug.2005 (Panel B of Table 6). Further, the OWP based on the model with $EE_{i,t}$ has a Sharpe ratio of 51.4% for the period Sep.2005-Dec.2015, compared with 42.3% for the OWP strategy based on the historical average returns (Panel C of Table 6).

We also verify whether the difference between the Sharpe ratios of different investment strategies is statistically significant. We compare the Sharpe ratio of each of the strategies with that of the SP and OWP strategies using a model that includes only the equilibrium error. We apply the block-bootstrap test of Ledoit & Wolf (2008) for testing $H_0 : \Delta = 0$ against $H_A : \Delta \neq 0$, where Δ is the difference between the S.R. of each strategy and the S.R. of the SP-$EE_{i,t}$ of col. (3) or the S.R. of the OWP-$EE_{i,t}$ of col. (7). The test of Ledoit & Wolf (2008) is valid under time series data, and it is robust to heavy-tailed return distributions. Their test statistic is obtained by resampling blocks (with a fixed length) of pairs of returns with replacement. We employ 1000 bootstrap replications with a block of size 5 to calculate the p-values of the test of Ledoit & Wolf (2008).

Table 6 shows that the Sharpe ratios of all strategies are significantly lower than that of the OWP-$EE_{i,t}$ at the 5% significance level, except for the OWP using the lagged returns and the OWP using the augmented model including $EE_{i,t}$. These findings are similar for the first subsample (Panel B of Table 6), in which the OWP-$EE_{i,t}$ outperforms almost all strategies at the 5% significance level. The relative performance of the OWP-$EE_{i,t}$ does not change in the second subsample, although the OWP-$EE_{i,t}$ outperforms only the historical average and buy-and-hold strategies at the 5% significance level (Panel C of Table 6). In sum, the Sharpe ratio of the OWP-$EE_{i,t}$ is the highest among all strategies for all sample and subsample periods so that the out-of-sample predictability of the equilibrium error has economic significance; the equilibrium error provides additional information about future excess industry returns relative to other predictors.

In addition, we find that strategies that consider the time-varying volatility of the returns are the best amongst the ones considered, in line with Liu (2007), Egloff et al. (2010), Zhou & Zhu (2012), Moreira & Muir (2017), and Moreira & Muir (2019). Our findings are also consistent with the results presented in Campbell & Viceira (1999), Barberis (2000), Wachter (2002), and Moreira & Muir (2019), who showed that long-term investors invest more in stocks under mean reversion of the stock returns. Accordingly, long-term investors perceive volatility increases as less than one-for-one increases in risk, because the mean-reverting component in stock returns implies that deviations today will be compensated by similar, opposite signed, movements in the near future. The OWP-$EE_{i,t}$ strategy considers only industry portfolios that are reverting, though in our case they revert to a long-term relationship with the market (not to a fixed constant like the mean), which justifies the better performance relative to buy-and-hold and benchmark strategies.

Table 7 in the Appendix presents the effect of transaction costs on the SP and OWP strategies. We allow for "high" transaction costs of 1%. Investors have to pay 1% of the return on industry portfolios if they switch from bonds to industry portfolios and 1% of the return on bonds if they switch from industry portfolios to bonds. We assure that we are imposing a high fee of 100-basis points since a 25-basis-point fee is in the upper range of transaction costs for the market index (Balduzzi & Lynch, 1999). Table 7 shows that the effects of imposing transaction costs on the SP and OWP strategies are negligible on their relative performance.

5. Conclusions

In this paper, we find that the dynamically estimated equilibrium error, the long-term common factor between industry portfolio and market cumulative returns, has strong predictive power for future excess industry portfolio returns. We identify the presence of a long-term relationship between an industry and the market by dynamically estimating a common stochastic trend using cointegration analysis. If there is no long-run common stochastic trends between them, then cointegration will not arise. We also investigate whether this relationship has predictive power for future returns in line with the models of gradual information diffusion across connected industries.

We corroborate the presence of predictive power of deviations from the equilibrium relationship by performing out-of-sample forecasting performance tests. We find that the equilibrium error has predictive ability for future excess industry portfolio returns even after including liquidity and risk control variables in the predictive regressions. Overall, our results support out-of-sample predictability of the equilibrium error to future excess industry portfolio returns.

In addition, we find a significantly negative effect of the equilibrium error on future industry returns, which is consistent with a long-term reversion to the equilibrium relationship between the selected US industry portfolios and the overall economy. In consonance with Hong et al. (2007) and Menzly & Ozbas (2010), information about the long-term relationship between an industry and the market is slowly incorporated into prices by uninformed investors, who do not invest using all public information available (Poterba & Summers, 1988). This gives rise to predictable reversion to the long-run relationship from the gradual incorporation of this information into market prices.

We also show that the out-of-sample explanatory power is economically meaningful for investors. Trading strategies implied by the proposed predictability provide portfolios with higher Sharpe ratios than a benchmark strategy does. Moreover, we find that the strategies that consider the time-varying volatility of the returns perform best among the ones we consider, in line with Liu (2007), Egloff et al. (2010), Zhou & Zhu (2012), Moreira & Muir (2017), and Moreira & Muir (2019). These results are robust in the presence of transaction costs when the investor pays a fee for switching his portfolio. Our results are conforming to Pesaran & Timmermann (1995), Guo (2006), and Johannes et al. (2014), who find economic gains from time-varying trading strategies. Therefore, investors can use the equilibrium error predictability to improve

Table 6

Returns of switching-portfolio and optimal-weighting portfolio strategies.

	Switching portfolio (SP) strategy				Optimal-weighting portfolio (OWP) strategy				
	$R_{i,t} - R_{f,t}$	$R_{i,t} - R_{f,t}$ & $EE_{i,t}$	$EE_{i,t}$	Hist. Av.	$R_{i,t} - R_{f,t}$	$R_{i,t} - R_{f,t}$ & $EE_{i,t}$	$EE_{i,t}$	Hist. Av.	B&H
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Aug.1995-Dec.2015									
Mean	.1987	.1944	.2012	.2030	.0390	.0397	.0357	.0513	.2375
S.D.	.4797	.4773	.4820	.4835	.0651	.0671	.0569	.1162	.5986
S.R.	.4142	.4073	.4174	.4198	.5989	.5923	**.6283**	.4414	.3968
$\hat{\Delta}$ w.r.t. SP-$EE_{i,t}$	-.0032	-.0101	-	.0024	.1815***	.1750***	.2110***	.0241	-.0206
LW p-value	(0.854)	(0.610)	-	(0.456)	(0.006)	(0.004)	(0.002)	(0.728)	(0.690)
$\hat{\Delta}$ w.r.t. OWP-$EE_{i,t}$	**-.2142***	**-.2210***	**-.2110***	**-.2086***	-.0295	-.0360	-	**-.1869***	**-.2316***
LW p-value	(0.002)	(0.001)	(0.002)	(0.001)	(0.559)	(0.454)	-	(0.001)	(0.008)
B. Aug.1995-Aug.2005									
Mean	.1991	.1972	.2116	.2148	.0530	.0533	.0459	.0613	.2586
S.D.	.5031	.5040	.5434	.5453	.0751	.0770	.0615	.1319	.6084
S.R.	.3958	.3913	.3894	.3940	.7064	.6923	**.7463**	.4649	.4251
$\hat{\Delta}$ w.r.t. SP-$EE_{i,t}$	.0064	.0019	-	.0000	.3170***	3029***	.3569**	.0755*	.0356
LW p-value	(0.843)	(0.950)	-	(1.000)	(0.002)	(0.003)	(0.029)	(0.089)	(0.711)
$\hat{\Delta}$ w.r.t. OWP-$EE_{i,t}$	**-.3506***	**-.3551***	**-.3569**	-.3524	-.0399	-.0540	-	**-.2814***	**-.3213**
LW p-value	(0.001)	(0.001)	(0.025)	(0.233)	(0.643)	(0.491)	-	(0.001)	(0.018)
C. Sep.2005-Dec.2015									
Mean	.1983	.1916	.1910	.1914	.0253	.0265	.0258	.0415	.2169
S.D.	.4579	.4517	.4155	.4164	.0503	.0528	.0503	.0980	.5906
S.R.	.4331	.4243	.4597	.4596	.5030	.5019	**.5137**	.4234	.3673
$\hat{\Delta}$ w.r.t. SP-$EE_{i,t}$	-.0266	**-.0354**	-	.0000	.0433	.0422	.0540	-.0363	**-.0924**
LW p-value	(0.175)	(0.078)	-	(0.981)	(0.600)	(0.596)	(0.424)	(0.407)	(0.051)
$\hat{\Delta}$ w.r.t. OWP-$EE_{i,t}$	-.0806	-.0894	-.0540	-.0541	-.0107	-.0118	-	**-.0903**	**-.1464**
LW p-value	(0.329)	(0.236)	(0.413)	(0.441)	(0.884)	(0.875)	-	(0.031)	(0.096)

Note: This table displays the mean, the standard deviation (S.D.), and the Sharpe ratio (S.R.) of the annualized returns of switching portfolio (SP) and optimal-weighting portfolio (OWP) strategies. For both strategies, we perform predictive regressions based on $R_{i,t} - R_{f,t}$ in cols. (1) and (5), on an augmented model with $EE_{i,t}$ in cols. (2) and (6), and on a model including only $EE_{i,t}$ in cols. (3) and (7) from the beginning of the sample up to time t, and we use the parameter estimates to forecast the excess return of each industry portfolio at time $t+1$. We also use the historical average (Hist. Av.) excess return estimated through period t, $\bar{R}_{i,t} - \bar{R}_{f,t}$, to forecast the excess return of each industry portfolio at $t+1$ in cols. (4) and (8). Forecasts are based on the updated sample in each subsequent time period.

We choose industry portfolios with positive expected excess returns, and we hold them during the following period under the SP strategy. We allocate a fraction of the portfolio in an industry portfolio based on the optimal weight of Equation (4) under the OWP strategy. We hold the market portfolio under the buy-and-hold (B&H) strategy (9). The strategies with the highest S.R. are in bold.

LW p-value is the block-bootstrap p-value of the test of Ledoit & Wolf (2008) of $H_0 : \Delta = 0$ against $H_A : \Delta \neq 0$, where Δ is the difference between the S.R. of each strategy and the S.R. of the SP-$EE_{i,t}$ of (3) ($\hat{\Delta}$ w.r.t. SP-$EE_{i,t}$) or the SR of the OWP-$EE_{i,t}$ of (7) ($\hat{\Delta}$ w.r.t. OWP-$EE_{i,t}$). We employ 1000 bootstrap replications with a block of size 5. The notation *, **, and *** indicate rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively. Significantly negative values of $\hat{\Delta}$ are also in bold.

out-of-sample portfolio performance.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. We downloaded the monthly return data for the 30 industry portfolios from Kenneth French's Data Library on `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. We obtained the monthly dividends on the S&P stock price index from Robert Shiller's website: `http://www.econ.yale.edu/~shiller/data.htm`. Finally, we gathered the daily S&P 500 composite price index (to calculate the market volatility) and the US consumer price index (to calculate the US inflation rate) from Data Stream and from the website of the Federal Reserve Bank of St. Louis (`https://fred.stlouisfed.org/`), respectively.

References

Asness, C. S., Porter, R. B., & Stevens, R. L. (2000). Predicting stock returns using industry-relative firm characteristics. Working Paper. Warrington College of Business at the University of Florida.

Balduzzi, P. & Lynch, A. W. (1999). Transaction costs and predictability: Some utility cost calculations. *Journal of Financial Economics*, *52*, 47–78.

Balvers, R., Wu, Y., & Gilliland, E. (2000). Mean reversion across national stock markets and parametric contrarian investment strategies. *The Journal of Finance*, *55*, 745–772.

Barberis, N. (2000). Investing for the long run when returns are predictable. *The Journal of Finance*, *55*, 225–264.

Bornholt, G., Gharaibeh, O., & Malin, M. (2015). Industry long-term return reversal. *Journal of International Financial Markets, Institutions and Money*, *38*, 65–78.

Bossaerts, P. (1988). Common nonstationary components of asset prices. *Journal of Economic Dynamics and Control*, *12*, 347–364.

Bossaerts, P. & Hillion, P. (1999). Implementing statistical criteria to select return forecasting models: What do we learn? *Review of Financial Studies*, *12*, 405–428.

Breen, W., Glosten, L. R., & Jagannathan, R. (1989). Economic significance of predictable variations in stock index returns. *The Journal of Finance*, *44*, 1177–1189.

Campbell, J. Y. & Shiller, R. J. (1988a). Interpreting cointegrated models. *Journal of Economic Dynamics and Control*, *12*, 505–522.

Campbell, J. Y. & Shiller, R. J. (1988b). Stock prices, earnings, and expected dividends. *The Journal of Finance*, *43*, 661–676.

Campbell, J. Y. & Shiller, R. J. (2005). *Valuation ratios and the long-run stock market outlook: An update*, volume 2, chapter 5, (pp. 173–201). Princeton University Press Princeton, NJ.

Campbell, J. Y. & Thompson, S. B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies*, *21*, 1509–1531.

Campbell, J. Y. & Viceira, L. M. (1999). Consumption and portfolio decisions when expected returns are time varying. *The Quarterly Journal of Economics*, *114*, 433–495.

Clark, T. E. & McCracken, M. W. (2001). Tests of equal forecast accuracy and encompassing for nested models. *Journal of Econometrics*, *105*, 85–110.

Clark, T. E. & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, *138*, 291–311.

Cohen, L. & Frazzini, A. (2008). Economic links and predictable returns. *The Journal of Finance*, *63*, 1977–2011.

Da, Z., Liu, Q., & Schaumburg, E. (2014). A closer look at the short-term return reversal. *Management Science*, *60*, 658–674.

De Bondt, W. F. M. & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, *40*, 793–805.

De Bondt, W. F. M. & Thaler, R. H. (1987). Further evidence on investor overreaction and stock market seasonality. *The Journal of Finance*, *42*, 557–581.

Egloff, D., Leippold, M., & Wu, L. (2010). The term structure of variance swap rates and optimal variance swap investments. *Journal of Financial and Quantitative Analysis*, *45*, 1279–1310.

Fama, E. F. (1991). Efficient capital markets: II. *The Journal of Finance*, *46*, 1575–1617.

Fama, E. F. & French, K. R. (1988). Permanent and temporary components of stock prices. *Journal of Political Economy*, *96*, 246–273.

Fama, E. F. & Schwert, G. W. (1977). Asset returns and inflation. *Journal of Financial Economics*, *5*, 115–146.

Gallagher, L. (1995). Interdependencies among the Irish, British and German stock markets. *The Economic and Social Review*, *26*, 131–147.

Goyal, A. & Welch, I. (2003). Predicting the equity premium with dividend ratios. *Management Science*, *49*, 639–654.

Granger, C. W. (1986). Developments in the study of cointegrated economic variables. *Oxford Bulletin of Economics and Statistics*, *48*, 213–228.

Gropp, J. (2004). Mean reversion of industry stock returns in the U.S., 1926–1998. *Journal of Empirical Finance*, *11*, 537–551.

Guo, H. (2006). On the out-of-sample predictability of stock market returns. *Journal of Business*, *79*, 645–670.

Hameed, A. & Mian, G. M. (2015). Industries and stock return reversals. *Journal of Financial and Quantitative Analysis*, *50*, 89–117.

Hjalmarsson, E. (2008). The Stambaugh bias in panel predictive regressions. *Finance Research Letters*, *5*, 47–58.

Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics*, *6*, 65–70.

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

Hong, H., Torous, W., & Valkanov, R. (2007). Do industries lead stock markets? *Journal of Financial Economics*, *83*, 367–396.

Inoue, A. & Kilian, L. (2004). In-sample or out-of-sample tests of predictability: Which one should we use? *Econometric Reviews*, *23*, 371–402.

Johannes, M., Korteweg, A., & Polson, N. (2014). Sequential learning, predictability, and optimal portfolio returns. *The Journal of Finance*, *69*, 611–644.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, *12*, 231–254.

Johansen, S. (1995). *Likelihood-Based Inference in Cointegrated Vector Auto-Regressive Models*. Oxford University Press.

Kanas, A. & Kouretas, G. P. (2005). A cointegration approach to the lead–lag effect among size-sorted equity portfolios. *International Review of Economics & Finance*, *14*, 181–201.

Kandel, S. & Stambaugh, R. F. (1996). On the predictability of stock returns: An asset-allocation perspective. *The Journal of Finance*, *51*, 385–424.

Kasa, K. (1992). Common stochastic trends in international stock markets. *Journal of Monetary Economics*, *29*, 95–124.

Künsch, H. R. (1989). The jackknife and the bootstrap for general stationary observations. *The Annals of Statistics*, *17*, 1217–1241.

Ledoit, O. & Wolf, M. (2008). Robust performance hypothesis testing with the Sharpe ratio. *Journal of Empirical Finance*, *15*, 850–859.

Lettau, M. & Ludvigson, S. (2001). Consumption, aggregate wealth, and expected stock returns. *The Journal of Finance*, *56*, 815–849.

Liu, J. (2007). Portfolio selection in stochastic environments. *The Review of Financial Studies*, *20*, 1–39.

Malin, M. & Bornholt, G. (2013). Long-term return reversal: Evidence from international market indices. *Journal of International Financial Markets, Institutions and Money*, *25*, 1–17.

McCracken, M. W. (2007). Asymptotics for out of sample tests of Granger causality. *Journal of Econometrics*, *140*, 719–752.

McQueen, G. (1992). Long-horizon mean-reverting stock prices revisited. *Journal of Financial and Quantitative Analysis*, *27*, 1–18.

Menzly, L. & Ozbas, O. (2010). Market segmentation and cross-predictability of returns. *The Journal of Finance*, *65*, 1555–1580.

Moreira, A. & Muir, T. (2017). Volatility-managed portfolios. *The Journal of Finance*, *72*, 1611–1644.

Moreira, A. & Muir, T. (2019). Should long-term investors time volatility? *Journal of Financial Economics*, *131*, 507–527.

Moskowitz, T. J. & Grinblatt, M. (1999). Do industries explain momentum? *The Journal of Finance*, *54*, 1249–1290.

Pástor, L. (2000). Portfolio selection and asset pricing models. *The Journal of Finance*, *55*, 179–223.

Pástor, L. & Stambaugh, R. F. (2000). Comparing asset pricing models: An investment perspective. *Journal of Financial Economics*, *56*, 335–381.

Pesaran, M. H. & Timmermann, A. (1995). Predictability of stock returns: Robustness and economic significance. *The Journal of Finance*, *50*, 1201–1228.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies*, *22*, 435–480.

Poterba, J. M. & Summers, L. H. (1988). Mean reversion in stock prices: Evidence and implications. *Journal of Financial Economics*, *22*, 27–59.

Rapach, D. E., Strauss, J. K., Tu, J., & Zhou, G. (2019). Industry return predictability: A machine learning approach. *The Journal of Financial Data Science*, *1*, 9–28.

Richards, A. J. (1997). Winner-loser reversals in national stock market indices: Can they be explained? *The Journal of Finance*, *52*, 2129–2144.

Shiller, R. J. (2015). *Irrational Exuberance: Revised and Expanded Third Edition*. Princeton, New Jersey: Princeton University Press.

Shleifer, A. & Vishny, R. W. (1992). Liquidation values and debt capacity: A market equilibrium approach. *The Journal of Finance*, *47*, 1343–1366.

Spierdijk, L., Bikker, J. A., & Van den Hoek, P. (2012). Mean reversion in international stock markets: An empirical analysis of the 20th century. *Journal of International Money and Finance*, *31*, 228–249.

Stambaugh, R. F. (1999). Predictive regressions. *Journal of Financial Economics*, *54*, 375–421.

Wachter, J. A. (2002). Portfolio and consumption decisions under mean-reverting returns: An exact solution for complete markets. *Journal of Financial and Quantitative Analysis*, *37*, 63–91.

Welch, I. & Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies*, *21*, 1455–1508.

Zhou, G. & Zhu, Y. (2012). Volatility trading: What is the role of the long-run volatility component? *Journal of Financial and Quantitative Analysis*, *47*, 273–307.

Appendix

Table 7
Returns of switching-portfolio and optimal-weighting portfolio strategies with transaction costs.

	Switching portfolio (SP) strategy				Optimal-weighting portfolio (OWP) strategy				
	$R_{i,t} - R_{f,t}$	$R_{i,t} - R_{f,t}$ & $EE_{i,t}$	$EE_{i,t}$	Hist. Av.	$R_{i,t} - R_{f,t}$	$R_{i,t} - R_{f,t}$ & $EE_{i,t}$	$EE_{i,t}$	Hist. Av.	B&H
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Aug.1995-Dec.2015									
Mean	.1716	.1673	.1734	.1752	.0390	.0397	.0357	.0513	.2375
S.D.	.4704	.4677	.4721	.4734	.0651	.0671	.0569	.1162	.5986
S.R.	.3647	.3577	.3674	.3700	.5989	.5923	**.6283**	.4414	.3968
$\hat{\Delta}$ w.r.t. SP-$EE_{i,t}$	-.0026	-.0097	-	.0026	.2315***	.2249***	.2610***	.0741**	.0294
LW p-value	(0.874)	(0.598)	-	(0.450)	(0.001)	(0.001)	(0.001)	(0.039)	(0.577)
$\hat{\Delta}$ w.r.t. OWP-$EE_{i,t}$	**-.4211*****	**-.4255*****	**-.4247*****	**-.4199*****	-.0295	-.0360	-	**-.1869*****	**-.3213*****
LW p-value	(0.001)	(0.001)	(0.001)	(0.001)	(0.532)	(0.449)	-	(0.001)	(0.006)
B. Aug.1995-Aug.2005									
Mean	.1573	.1555	.1689	.1719	.0530	.0533	.0459	.0613	.2586
S.D.	.4837	.4846	.5251	.5267	.0751	.0770	.0615	.1319	.6084
S.R.	.3253	.3208	.3216	.3264	.7064	.6923	**.7463**	.4649	.4251
$\hat{\Delta}$ w.r.t. SP-$EE_{i,t}$	.0037	-.0008	-	.0000	.3848***	.3707***	.4247***	.1433***	.1035
LW p-value	(0.911)	(0.975)	-	(1.000)	(0.001)	(0.001)	(0.001)	(0.008)	(0.278)
$\hat{\Delta}$ w.r.t. OWP-$EE_{i,t}$	**-.4211*****	**-.4255*****	**-.4247*****	**-.4199*****	-.0399	-.0540		**-.2814*****	**-.3213****
LW p-value	(0.001)	(0.001)	(0.001)	(0.006)	(0.604)	(0.488)	-	(0.001)	(0.013)
C. Sep.2005-Dec.2015									
Mean	.1855	.1788	.1779	.1783	.0253	.0265	.0258	.0415	.2169
S.D.	.4586	.4523	.4161	.4171	.0503	.0528	.0503	.0980	.5906
S.R.	.4044	.3954	.4276	.4276	.5030	.5019	**.5137**	.4234	.3673
$\hat{\Delta}$ w.r.t. SP-$EE_{i,t}$	-.0231	**-.0321***	-	.0000	.0754	.0744	.0861	-.0042	-.0603
LW p-value	(0.243)	(0.073)	-	(0.968)	(0.401)	(0.403)	(0.253)	(0.928)	(0.190)
$\hat{\Delta}$ w.r.t. OWP-$EE_{i,t}$	-.1093	-.1183	-.0861	-.0861	-.0107	-.0118		**-.0903****	**-.1464***
LW p-value	(0.227)	(0.171)	(0.238)	(0.257)	(0.863)	(0.870)	-	(0.047)	(0.096)

Note: This table displays the mean, the standard deviation (S.D.), and the Sharpe ratio (S.R.) of the annualized returns of switching portfolio (SP) and optimal-weighting portfolio (OWP) strategies with the same specifications of Table 6. We assume that investors pay a fee of 1% of the return on industry portfolios on switching from bonds to industry portfolios and a fee of 1% of the return on bonds on switching from industry portfolios to bonds.
LW p-value is the block-bootstrap p-value of the test of Ledoit & Wolf (2008) of $H_0 : \Delta = 0$ against $H_A : \Delta \neq 0$, where Δ is the difference between the S.R. of each strategy and the S.R. of the SP-$EE_{i,t}$ of (3) ($\hat{\Delta}$ w.r.t. SP-$EE_{i,t}$) or the SR of the OWP-$EE_{i,t}$ of (7) ($\hat{\Delta}$ w.r.t. OWP-$EE_{i,t}$). We employ 1000 bootstrap replications with a block of size 5. The notation *, **, and *** indicate rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively. Significantly negative values of $\hat{\Delta}$ are also in bold.