Volatility of Price-Earnings Ratio and Return Predictability

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Abstract

We introduce a novel second-order dynamic price-earnings ratio model and demonstrate that both the level and volatility of the price-earnings ratio serve as optimal forecasts of future returns, cash flow growth, and market volatility. We show that the volatility of the log price-earnings ratio predicts positive future stock returns with both statistical and economic significance, in various horizons and frequencies, and both in-sample and out-of-sample. The volatility of the price-earnings ratio outperforms both the level of the price-earnings ratio and market volatility in predicting returns. Additionally, we find that the volatility of the log price-earnings ratio significantly predicts declines in future macroeconomic activities and market volatility. The superior predictability of price-earnings ratio volatility reflects the information on uncertainty and risk from both the market and fundamentals. Further analysis suggests that at the ten-year horizon, the return predictive power of volatility of the log price-earnings ratio can be attributed to future cash flow shocks, discount rate shocks, and volatility shocks. At shorter horizons, however, the predictive power cannot be fully explained by these factors.

Keywords: Volatility of Price-Earnings Ratio; Predicting Market Equity Premium, Macroeconomic Activities; Market Volatility; Cash Flow Shocks; Discount Rate Shocks; Volatility Shocks.

JEL: E17, E44, G12, G14

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1 Introduction

Contemporary research on asset pricing asserts that the expected aggregate market risk premium is not constant but rather varies over time, suggesting that aggregate market risk premium is predictable. Consistent with this perspective, the asset pricing literature underscores the importance of stochastic volatility in determining asset prices and bears a distinct risk premium (e.g., Merton, 1980, Bloom, 2009, Bansal et al., 2014, and Campbell et al., 2018). There is, however, limited empirical evidence supporting time-series return predictability of volatility (measured either based on macro fundamentals or market returns), particularly in long-run.[1] In this paper, we propose a novel second-order dynamic price-earnings ratio model in the similar spirit of Gao and Martin (2021), and argue that both the level and the volatility of price-earnings ratio serve as the optimal forecast of future market returns, cash flow growths, and volatility risk, presenting valuable new paths for comprehending the dynamic accounting identity and return predictability.

Consistent with our model, we find that the volatility of the log price-earnings ratio (V_{pe}) significantly predicts future positive market returns, future declines in macroeconomic activities (such as GDP growths, consumption growths, and net cash flow growths), and future decreases in long-term market volatility. The return predictability is both statistically and economically significant, remaining robust across market excess and real returns, at various horizons, frequencies and sample periods, holding both in-sample and out-of-sample, and accounting for control variables. The predictive power of V_{pe} outperforms that of log price-earnings ratio (pe), the volatility of market excess returns (V_{re}), and the volatility of market real returns (V_{rr}). Further analysis indicates that the superior predictability can be attributed to the plausible linkage between V_{pe} and quantity of risk, as well as price of risk. To the best of our knowledge, this is the first study analyzing the predictability of market returns, macroeconomic activities, and market volatility using V_{pe}.

Our paper is motivated by the second-order dynamic price-dividend ratio model presented in Gao and Martin (2021) who extend Campbell and Shiller (1988) loglinear dynamic dividend growth model and allow the second moment of log price-dividend ratio to play an important role in comprehending the dynamic accounting identity, particularly when the price-dividend ratio is

[1] Guo (2006) presents empirical evidence showing that aggregate market return volatility joined with consumption-wealth ratio (*cay*) exhibit significant return predictive power while aggregate market return volatility alone displays negligible predictive power. Martin (2017) presents evidence of short-run return predictability using a lower bound on the equity premium, $SVIX^2$, based on option data.

persistent and far deviated with its long-run mean. We further elaborate on the dynamic accounting identity by Gao and Martin (2021) in two distinct dimensions. First, we relax the homoscedasticity assumption of the price-dividend ratio in Gao and Martin (2021), allowing the price-earnings ratio and its volatility to reflect not only expected future cash flow growth and discount rates but also conditional future stochastic volatility. Second, we shift our focus on price-earnings ratio instead of price-dividend ratio for several reasons. Empirical evidence shows unstable dividend policy (e.g., Fama and French, 2001; and Vuolteenaho, 2002) and stronger connection between earnings and economic activities and fundamentals (e.g., Penman and Sougiannis, 1998 and Konchitchki and Patatoukas, 2014), as well as better return predictability of price-earnings ratio compared to price-dividend ratio(e.g., Campbell and Shiller, 2005). In light of this observation, we propose a novel second-order dynamic price-earnings ratio model following a similar approach as Gao and Martin (2021). This model presents a three-factor structure that both pe and V_{pe} are endogenously associated with the long-run future market returns (risk premium), long-run future growths, and/or long-run volatility.

We argue that V_{pe} better captures the inherent uncertainty and forward-looking in stochastic volatility of market returns and fundamentals. First, the nature of conditional volatility is unobservable or latent, and time-varying. Many empirical estimates of conditional volatility rely on realized returns or realized fundamentals. A growing list of studies explores ex ante measure of expected returns using valuation ratios (e.g., Claus and Thomas, 2001; Easton, 2004; Polk et al., 2006; Kelly and Pruitt, 2013; Jagannathan and Marakani, 2015; and Jiang and Kang, 2020). V_{pe} reflects the inherent uncertainty and forward-looking nature in expected return volatility if pe ratio is a reasonable proxy for the expected returns.[2] Second, V_{pe} captures the information on the uncertainty and risk from both market and fundamental factors (e.g., Bansal and Yaron, 2004 and Ghosh and Constantinides, 2021). Third, the predictability of the V_{pe} is a direct implication of the second-order dynamic price-earnings ratio model.

Our paper contributes to the return predictability literature by demonstrating that V_{pe} as a proxy for the volatility of expected returns significantly and robustly predicts positive market returns. Numerous studies have found, though with controversy, that market expected returns

[2] In a recent study, Ai et al. (2022) propose and examine the information-driven volatility measured as variance of expected macroeconomic fundamentals, showing that the information-driven volatility induces a negative correlation between past realized volatility and future expected returns.

are time-varying and predictable with various variables (e.g., Ang and Bekaert, 2007; Cochrane, 2008; Goyal and Welch, 2008; Campbell and Thompson, 2008; Rapach et al., 2010; Koijen and Van Nieuwerburgh, 2011; Zhou and Zhu, 2015; Yang, 2023; Gao and Martin, 2021; Goyal et al., 2021; Cederburg et al., 2023; and Bali et al., 2023; among others). Cederburg et al. (2023) provides an insightful discussion on the economic significance of stock market return predictability. While the existing studies provide comprehensive evaluation on return predictability using various predictors, this study represents the initial exploration of return predictability through the analysis of V_{pe}. We identify a new predictor, V_{pe}, which exhibits substantial and consistent predictability for future market returns and macroeconomic activities.

A growing literature emphasizes the effect of stochastic volatility in macroeconomics and finance. Bansal et al. (2014) and Campbell et al. (2018) develop an intertemporal asset pricing model with stochastic volatility and demonstrate that volatility risk is indeed an important and separate risk that significantly affects the macroeconomic activities and asset prices. The volatility risk, beyond cash flow risk and discount rate risk, is priced in the cross-section of stock returns. These studies measure stochastic volatility relying on realized market returns or macroeconomic activities (also see Zhou and Zhu, 2015) and concentrate on examining the impact of stochastic volatility on the cross-section of stock returns. We introduce V_{pe} as a novel measure of stochastic volatility. We emphasize the aggregate time-series dynamic relation between V_{pe}, expected market risk premium, macroeconomic activities, and stochastic volatility. The time-series predictability using V_{pe} substantially surpasses that achieved through the volatility of realized returns, complementing the cross-sectional study on stochastic volatility.

Our paper also relates to the literature on empirical tests of risk-return trade-off relation. The main challenge in testing the risk-return trade-off relation (e.g., Merton, 1980) is that the expected market return and the conditional volatility of the market are not observable. To better understand the inherent stochastic nature of conditional volatility, researchers explore various methods involving statistical models, econometric techniques, or other proxies (e.g., Glosten et al., 1993; Harvey, 2001; Ghysels et al., 2005; Constantinides and Ghosh, 2011; Jiang and Lee, 2014; among others). Scruggs (1998), Guo (2006), and Guo and Whitelaw (2006) argue that the misspecification problem caused by omitted variables leads to weak or negative risk-return relation. Using the volatility of the log price-earnings ratio as a measure of the volatility of expected returns, we provide additional positive risk-return trade-off evidence consistent with Merton (1980).

The rest of the paper is organized as follows. Section 2 outlines our framework. We discuss data and the construction of volatility of log price-earnings ratio in Section 3. Section 4 presents our main empirical results. Section **??** explores the potential sources of predictability and we conclude in Section 6.

2 Framework

We start with the loglinear present value identity of Campbell and Shiller (1988). Let P_{t+1}, D_{t+1}, and R_{t+1} be the price, dividend, and gross return of the market, respectively, we define gross return as:

$$R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t} = \frac{P_{t+1} + D_{t+1}}{D_{t+1}} \frac{D_{t+1}}{D_t} \frac{D_t}{P_t} \tag{1}$$

Taking logarithm of both sides of equation (1) yields:

$$r_{t+1} = \Delta d_{t+1} - pd_t + log(1 + e^{pd_{t+1}}) \tag{2}$$

where $pd_t = p_t - d_t = log(P_t) - log(D_t)$ and $\Delta d_{t+1} = d_{t+1} - d_t$.

Applying the first-order Taylor approximation to linearize the last term in equation (2), Campbell and Shiller (1988) derive that the log of the price-dividend ratio can be expressed as a linear function of expected future returns and expected dividend growth rates; that is

$$pd_t = k + \sum_{j=0}^{\infty} \rho^j E_t(\Delta d_{t+1+j} - r_{t+1+j}), \tag{3}$$

where lowercase letters denote logs of the corresponding uppercase letters, $pd_t = p_t - d_t$, $\Delta d_{t+j+1} = d_{t+j+1} - d_{t+j}$, and $\rho = \frac{\mu}{1+\mu}$, where $\mu = e^{\bar{pd}}$, and $k = \frac{log(1+\mu) - \rho log(\mu)}{1-\rho}$. Equation (3) demonstrates that the log price-dividend ratio provides the optimal forecast of the long-run growth rates and long-run returns.

Gao and Martin (2021) expand upon the present value identity of Campbell and Shiller (1988) using the second-order Taylor expansion and allow the second movement of log price-dividend ratio to enter the present value identity. Assuming that the log price-dividend ratio follows an AR(1) process: $pd_{t+1} - \bar{pd} = \phi(pd_t - \bar{pd}) + \epsilon_{t+1}$, where $var_t \epsilon_{t+1} = \sigma^2$, Gao and Martin (2021) derive the following novel present value identity:

$$pd_t = \alpha + \sum_{j=0}^{\infty} \rho^j E_t(g_{d,t+1+j} - r_{t+1+j}) + \frac{\rho(1-\rho)\phi^2}{2(1-\rho\phi^2)} var(pd_t) \tag{4}$$

where $var(pd_t)$ denotes the variance of log price-dividend ratio and $\alpha = k + \frac{\rho\sigma^2}{2(1-\rho\phi^2)}$. Gao and Martin (2021) view the variance of log price-dividend ratio as convexity correction, and show that the variance of log price-dividend ratio can be quantitatively important when price-dividend ratio is persistent and deviates far away from its mean.

In this study, we propose a novel second-order dynamic price-earnings ratio model, expanding upon the work of Gao and Martin (2021) in two key aspects. First, we emphasize on price-earnings ratio rather than price-dividend ratio. Corporate dividend policies are widely recognized for their instability and modeling challenge with many firms refraining from paying dividends in their early stages (e.g., Fama and French, 2001; and Vuolteenaho, 2002). In addition, earnings are more directly related to economic activities and fundamentals, and better predict future stock returns than price-dividend ratio (e.g., Penman and Sougiannis, 1998; and Konchitchki and Patatoukas, 2014). Price-earnings ratio also shows better return predictability (Campbell and Shiller, 2005). Second, to explore the information content of V_{pe}, we relax the homoscedasticity assumption in Gao and Martin (2021) and allow stochastic volatility reflecting time-varying economic uncertainty to enter the dynamic identity.

Following Nelson (1999) and Sharpe (2002), we express log price-dividend ratio (pd_t) as log price-earnings ratio (pe_t) and log dividend payout ratio (λ_t). Dividend smoothing is one of the most well-documented phenomena in corporate financial policy. Lintner (1956, 1963) observes that firms are primarily concerned with the stability of dividends and attempt to make adjustments of dividends toward some desirable (target) payout ratio. Here, since our interest is the volatility of price-earnings ratio, we model the dividend payout ratio (Λ_t) as the long-term target ratio ($\bar{\Lambda}$) times a random variable (Γ_t) for simplicity: $\Lambda_t = \bar{\Lambda}\Gamma_t$, and $\gamma_t \equiv log(\Gamma_t) \sim N(0, \kappa^2)$. Formally,

$$pd_t = pe_t - \lambda_t \tag{5}$$

where $\lambda_t = log(\Lambda_t) = log(\bar{\Lambda}) + \gamma_t$.[3]

Denoting the aggregate earning of the market by E, equation (2) can be rewritten as:

$$r_{t+1} = \Delta e_{t+1} + \lambda_{t+1} - pe_t + log(1 + e^{pe_{t+1} - \lambda_{t+1}}) \tag{6}$$

where $\Delta e_{t+1} = e_{t+1} - e_t = log(E_{t+1}) - log(E_t)$.

Following Gao and Martin (2021) and taking a second-order Taylor expansion, we derive the following novel present value identify:

$$pe_t = \delta^* + E_t[\sum_{j=0}^{\infty} \rho^j (\Delta e_{t+1+j} - r_{t+1+j})] + \frac{1}{2}\rho(1-\rho)E_t[\sum_{j=0}^{\infty} \rho^j (pe_{t+1+j} - \bar{pe})^2] \tag{7}$$

where $\rho = \frac{e^{\bar{pe} - \bar{\lambda}}}{1 + e^{\bar{pe} - \bar{\lambda}}} = \frac{e^{\bar{pd}}}{1 + e^{\bar{pd}}} > 0$, and $\delta^* = \frac{1}{2}\rho\kappa^2 + \frac{k - \rho\bar{pe} + \bar{\lambda}}{1-\rho}$, all are constant. $\bar{pe}$ and $\bar{\lambda}$ are defined as the aggregate mean of log price-earnings ratio and log long-term target dividend payout ratio.

Similar to Gao and Martin (2021), we assume that log price-earnings ratio follows AR(1) process. However, we relax the homoscedasticity assumption in Gao and Martin (2021) and allow time-varying conditional volatility of a state variable in the economy. This assumption is motivated by asset pricing theory. The habit model in Campbell and Cochrane (1999) reveals that time-varying risk aversion directly affects time-varying price-dividend ratio (price-earnings ratio). The fluctuation of risk aversion over time is associated with higher volatility of price-earnings ratio, and then higher expected returns. On the other hand, Bansal and Yaron (2004)'s long-run risk model indicates that the volatility of valuation ratios can be attributed to variation in expected growth rates and fluctuating economic uncertainty (conditional volatility of consumption). Accordingly we model the dynamics of price-earnings ratio as AR(1) process with the time-varying stochastic volatility. That is:

$$pe_{t+1} - \bar{pe} = \phi(pe_t - \bar{pe}) + \psi\sigma_t u_{t+1}, \tag{8}$$

where $u_{t+1} \sim Ni.i.d(0,1)$ and σ_t denotes the stochastic volatility reflecting time-varying economic uncertainty. Substituting equation (8) into equation (7), we obtain the following second-order

[3] Empirically, the aggregate long-term target dividend payout ratio ($\bar{\Lambda}$) is about 0.55 over the sample period of 1927 - 2021, and the regression of log dividend payout ratio (λ_t) on the constant shows a high R^2 of 0.81.

dynamic price-earnings ratio model [4]:

$$pe_t - \pi E_t[(pe_{t+1} - \bar{pe})^2] = \delta^* + E_t[\sum_{j=0}^{\infty} \rho^j (\Delta e_{t+1+j} - r_{t+1+j} + \nu\sigma^2_{t+1+j})] \quad (9)$$

where $\pi = \frac{\rho(1-\rho)}{2(1-\rho\phi^2)}, \nu = \frac{\psi^2\rho(1-\rho)}{2(1-\rho\phi^2)}$, and $E_t[(pe_{t+1} - \bar{pe})^2]$ is the conditional volatility of log price-earnings ratio. Even though the unconditional volatility of pe ratio is constant, the conditional volatility of pe ratio is time-varying. In the empirical work below, we use both the variance and standard deviation of ten-year rolling log S&P price-earnings ratio as a proxy for the conditional volatility of pe ratio. It is worth emphasizing that equation (9) closely aligns with three risk factors, cash flow risk, discount rate risk, and volatility risk, emphasized in Bansal et al. (2014) and Campbell et al. (2018). It states that both the level and volatility of log price-earnings ratio exhibit the optimal forecast of the long-run earnings growths, long-run expected returns and long-run volatility. It highlights the importance of the second movement of price-earnings ratio and provides valuable new paths for comprehending the dynamic accounting identity and return predictability.

3 Data

In our empirical analysis, we use an annual sample from 1937 to 2023.[5] Market returns (R_m) are from CRSP value-weighted market returns, while stock market prices (P), dividends (D, four-quarter moving sum of dividends), and earnings (E, four-quarter moving sum of earnings) of the Standard and Poor's (S&P) 500 index are from Robert J. Shiller's website. The risk-free rates (R_f) are measured as one-month T-bill rates from CRSP. Inflation rates are based on the Consumer Price Index from the Bureau of Labor Statistics.

The log price-earnings (pe) ratio is measured as the difference between the log of price and the log of earnings. The stock market excess returns (R_e) and real returns (R_r) are measured as the difference between the stock market returns and risk-free rates as well as the difference between market returns and inflation rates. We construct the volatility of log price-earnings ratio (V_{pe}) as the variance and standard deviation of log price-earnings ratios using a previous ten-year rolling

[4] Detailed derivation can be found in the Appendix.

[5] Our original sample is from 1927 to 2023. Due to the construction of volatility, we lose ten years of observations. The testing data sample period is from 1937 to 2023.

window. The same approach is applied to the volatility of excess returns (V_{re}) and the volatility of real returns (V_{rr}).[6] We use ten-year rolling window for volatility construct volatility due to two main reasons. First, our model suggests that V_{pe} is associated with the expected long-run future market returns, cash flows, and stochastic volatility. Using the relatively long window helps capture this long-run relationship. Second, Asness (2000) argues that investors' perception of equity risk is influenced by volatility observed over time, advocating a rolling twenty-year return volatility. To capture the long-run component of the volatility, we select 10-year window for volatility estimation.[7] The relatively long window, smoothing out short-run transitory component, tends to reveal information on long-run risk. Summary statistics for these variables are presented in Table 1.

In Panel A, we report mean, standard deviation, first-order autocorrelation, and unit-root tests based on the augmented Dickey-Fuller test(Dickey and Fuller, 1979) and the Philips-Perron test(Phillips and Perron, 1988) of these variables. All variables considered appear stationary, with first-order autocorrelation coefficients below 0.9. We are particularly interested in the property of V_{pe}. The null hypothesis of a unit root has been statistically rejected in both augmented Dickey-Fuller test and Philips-Perron test. The V_{pe} shows reasonable persistence with the AR(1) coefficient of 0.853, lower than the coefficients of the volatility of excess returns (V_{re}) and volatility of real returns (V_{rr}). The V_{pe} has a higher mean and a slightly higher standard deviation compared to V_{re} and V_{rr}. In Panel B, we report a correlation matrix between the considered variables. The pe, as expected, is positively correlated with excess returns and real returns and negatively correlated with various volatility measures. V_{re} and V_{rr} are highly correlated with the coefficient of 0.975. V_{re} (V_{rr}) is negatively correlated to excess returns (real returns) with notably smaller values. The correlation between V_{re} and excess returns is -0.034 and the correlation between V_{rr} and real returns is -0.051. It is interesting to note that V_{pe} is positively correlated with both market returns (R_e and R_r) and realized market volatility (V_{re} and V_{rr}). The correlations between V_{pe} and R_e and between V_{pe} and R_r are 0.250 and 0.182, respectively, while the correlations between V_{pe} and V_{re} and between V_{pe} and V_{rr} are 0.318 and 0.369, respectively.

V_{pe} is quite volatile and persistent in our sample period. We plot V_{pe} with one-year, five-year,

[6] The empirical results are qualitatively similar when using either variance or standard deviation of price-earnings ratio. To save space, we report results based on the standard deviation only; results using variance are available upon request.

[7] The results are robust when the volatility of pe ratio is estimated using 7-year and 15-year windows.

seven-year, and ten-year ahead stock market excess returns in Figure 1. We find that V_{pe} shows similar long up and down swings as long-run returns. The property of slow mean reversion in V_{pe} hints at long-run return predictability.

4 Predicting equity market returns, macroeconomic activities, and market volatility

4.1 In-sample return prediction

We primarily employ the OLS predictive regressions in our in-sample analysis. However, as well-documented in the return predictability literature, predictive regressions pose certain serious econometric issues (e.g., Granger and Newbold, 1974; Mark, 1995; Nelson and Kim, 1993; Stambaugh, 1999; Lewellen, 2004, and Kostakis et al., 2015). To mitigate potential heteroskedasticity and autocorrelation concerns, we calculate and report Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard error (computed with lags set to the number of horizons plus one) for parameter estimates. To address the statistical issue with overlapping data in long-horizon predictive regressions, we calculate and report Hodrick (1992) standard error. Stambaugh (1999) shows that there is a small sample bias in the estimated predictive coefficient in forecast regressions with price-scaled variables, particularly when they are highly persistent (also see Amihud and Hurvich, 2004 and Amihud et al., 2008). Although our key predictor, V_{pe}, is not a price-scaled variable per se, and the null hypothesis of a unit root has been statistically rejected, it is quite persistent. To remedy this issue, we apply the bootstrap procedure, impose the null of no predictability in calculating the critical values, and report the bootstrap p-values for each parameter estimate.

The second-order dynamic price-earnings ratio model in Equations (9) implies that both the level and the volatility of pe are associated with future market returns, cash flow growths and volatility. However, few studies have investigated the return predictability using V_{pe}. Guo (2006) and Guo and Savickas (2006) document that predicting market returns based solely on aggregate stock market volatility yields little predictive ability. However, market volatility jointly with either idiosyncratic volatility or consumption wealth ratio (cay) by Lettau and Ludvigson, 2001 exhibits strong predictive power for market excess return, supporting positive risk-return relation. For comparison, we also examine the return predictability of the volatility of excess returns and the volatility of real returns. We report forecast regression coefficients, Newey-West corrected standard errors (Newey and West, 1987), Hodrick standard errors (Hodrick, 1992), bootstrapping p-value and adjusted R^2 statistics.

4.1.1 Univariate return prediction

We start with the in-sample prediction by conducting the following univariate long-horizon predictive regression:

$$R_{t,t+k} = \alpha_k + \beta_k x_t + \epsilon_{t+k}. \tag{10}$$

where $R_{t,t+k}$ is the compounded excess return (R_e) or real return (R_r) in k years in the future, and x_t represents a predictive variable known at time t, which includes pe, V_{re}, V_{rr}, and V_{pe}, respectively. The predictive horizons are 1, 3, 5, 7, and 10 years ahead, respectively.

The results for the univariate long-horizon predictive regressions for excess return and real return are presented in Table 2. Whether using R_e or R_r as the dependent variable, we find that pe predicts future market returns negatively while V_{pe} predicts market returns positively, consistent with our second-order dynamic price-earnings ratio model. V_{re} and V_{rr} exhibit little return predictability. V_{pe} significantly predicts R_e and R_r at each horizon, from one year to ten years ahead. The positive relation between V_{pe} and future market returns is consistent with the positive risk-return relation (e.g., Merton, 1980). The adjusted R^2 monotonically increases as the number of prediction horizons increases. The return predictability performance of Vpe is superior than that of pe, V_{re}, and V_{rr}.

We focus on the return predictability of V_{pe}. V_{pe} predicts 5.3% of the variation of market excess returns one-year ahead; the predictive coefficient is 0.605 with a Newey-West standard error of 0.213, Hodrick standard error of 0.298, and bootstrapping p-value of 0.014. In the three-year horizon, V_{pe} predicts 18.4% of the variation of market excess returns; the predictive coefficient is 1.874 with a Newey-West standard error of 0.439, Hodrick standard error of 0.811, and bootstrapping p-value of 0.000. For five-year ahead forecast, 25.9% of the variation of market excess returns is predicted by V_{pe}; the predictive coefficient is 3.319 with a Newey-West standard error of 0.795, Hodrick standard error of 1.282, and bootstrapping p-value of 0.000. In seven-year horizon, V_{pe} predicts 29.4% of the variation of market excess returns; the predictive coefficient is 4.823 with a

Newey-West standard error of 1.260, Hodrick standard error of 1.631, and bootstrapping p-value of 0.000. Finally, in ten-year horizon, V_{pe} predicts 33.3% of the variation of market excess returns; the predictive coefficient is 8.570 with a Newey-West standard error of 2.430, Hodrick standard error of 2.002, and bootstrapping p-value of 0.000. Similar results are found when the dependent variable is market real return. Similarly, V_{pe} significantly predicts positive real returns (R_r) in each of the horizons, from one-year ahead to ten-year ahead. The adjusted R^2 monotonically increases as the number of prediction horizons increases, spanning from 3.2% in one-year horizon to 29.3% in ten-year horizon.

V_{re}, in contrast, shows no return predictability over one-year, three-year, or five-year horizons. In seven-year and ten-year horizons, it, however, exhibits moderate return predictability with adjusted R^2 of 2.7% and 8.2%, respectively. V_{rr} performs even worse, showing no return predictability in any prediction horizon. Our result of poor performance on return predictability of V_{re} and V_{rr} is consistent with the empirical work of the univariate predictive regression in Guo (2006) and Guo and Savickas (2006). The superior performance of return predictability using V_{pe} compared to V_{re} and V_{rr} suggests that V_{pe} better captures time-varying market risk premium than V_{re} and V_{rr}. Plausibly, V_{pe} contains information on both the uncertainty of the market and the uncertainty of fundamentals. We also examine the return predictability of volatility of log price-dividend ratio (V_{pd}), variance risk premium (vrp) in Bollerslev et al. (2009), and stock variance ($svar$) in Guo and Whitelaw (2006) in Table B.1. V_{pd} exhibits no predictability in one-year, three-year, or five-year horizons and moderate return predictability in seven-year and ten-year horizons for excess returns, while no predictability at all horizons for real returns, possibly due to the smoothness of aggregate dividend (Chen et al., 2012). It is not surprising that vrp exhibits no predictability at all horizons for both excess returns and real returns since annual frequency data is used here and vrp typically shows short-run return predictability up to six months (e.g., Carr and Wu, 2008; Bollerslev et al., 2009; and Song and Taamouti, 2017). $svar$ also shows poor performance in predicting market returns, with only some predictability in three-year or five-year horizon.

As a robustness check, we run a similar univariate forecast regression using quarterly frequency data with predictive horizons of 1, 2, 3, 4, 12, 20, 28, and 40 quarters. Table 3 reports the results. Consistent with the findings in Table 2, Table 3 shows that V_{pe} significantly predicts market excess returns and real returns across all horizons considered, and the return predictability performance of Vpe is superior than that of pv, V_{re}, and V_{rr}.

The return predictability using valuation ratios appears to be unstable (e.g. Ang and Bekaert, 2007, Lettau et al., 2008, Lettau and Van Nieuwerburgh, 2008, Goyal and Welch, 2008). To examine whether the return predictability using V_{pe} exhibits instability, also for the purpose of conducting robustness checks, we explore different sample periods. In Table 4, using four different subsamples, 1937-1999 (excluding Tech Bubble, 2008 Financial Crisis, and Covid-19), 1937-2007 (excluding 2008 Financial Crisis and Covid-19), 1937-2019 (excluding Covid-19) and 1950-2023 (excluding World War II), we examine the stability of return predictability using V_{pe}.

Panel A of Table 4 reports the results when applying market excess return as the dependent variable. pe ratio significantly predicts future returns with a negative coefficient in different subsamples, 1937-1999, 1937-2007 and 1937-2019, respectively. However, in the 1950-2023 subsample, pe ratio shows insignificant predictability in one-year, three-year, and five-year horizons. The adjusted R^2s of univariate regression using pe are 4.0%, 6.4%, 3.3% and 0.5% in the one-year horizon, and 27.9%, 28.3%, 22.8% and 9.8% in the ten-year horizon, for the subsample period 1937-1999, 1937-2007, 1937-2019 and 1950-2023, respectively. This evidence is consistent with the unstable return predictability using valuation ratios in the literature. V_{re} shows insignificant return predictability at the 5% level for any prediction horizon and subsample except for the ten-year horizon in the subsamples from 1937 to 2007 and from 1937 to 2019. In contrast, V_{pe} predicts future excess returns with a significantly positive coefficient in each horizon and each subsample. The predictability seems relatively stable across different subsamples. The adjusted R^2s of one-year ahead prediction regression using V_{pe} are relatively stable, 6.7%, 6.9%, 5.9% and 4.4%, for the subsample period 1937-1999, 1937-2007, 1937-2019 and 1950-2023, respectively, and 33.5%, 33.7%, 32.7% and 31.7%, for the subsample period 1937-1999, 1937-2007, 1937-2019 and 1950-2023, respectively, in the ten-year horizon. The results reported in Panel B using real return as a dependent variable are qualitatively similar.

Lundblad (2007) argues that the primary challenge in estimating the risk-return relationship is due to small samples. Using information from a longer historical record of the U.S. and U.K. equity market experience, Lundblad (2007) presents a significantly positive risk-return relationship. Following Lundblad (2007), we examine the return predictability of V_{pe} using the longer sample of S&P index data from Robert J. Shiller's website to extend our sample period back to 1881.

Due to the lack of available risk-free rate data, we use real returns as the dependent variable and report the results in Table 5. *pe* ratio significantly predicts future real returns with a negative coefficient in ten-year horizon but loses the statistical significance in other horizons. V_{rr} displays no predictability for any horizon. In contrast, our V_{pe} consistently predicts the positive S&P real returns in every horizon with a significant level of at least 5%. This robustness check confirms that the return predictive power of V_{pe} is both superior and consistently stable.

4.1.2 Multivariate return prediction

Next we examine whether the return predictability of V_{pe} can be subsumed by existing predictors. For this purpose, we execute the following multivariate predictive regression:

$$R_{t,t+k} = \alpha_k + \beta_k V_{pe,t} + \theta_k x_t + \epsilon_{t+k}. \tag{11}$$

where $R_{t,t+k}$ is the k-period ahead cumulative compounded excess return, V_{pe} denotes the volatility of *pe* ratio. x denotes a set of control variables. The forecast horizons are 1, 3, 5, 7, and 10 years ahead, respectively. We consider two sets of control variables. First, Equation (9) states that both level and volatility of *pe* ratio provide the optimal forecast of the long-run expected returns. In addition, we want to compare the return predictability between V_{pe} and $V_{re}(V_{rr})$. In the first set of controls, we examine three pairs of predictors: *pe* and $V_{re}(V_{rr})$, *pe* and V_{pe}, and V_{re} (V_{rr}) and V_{pe}, separately. The second set of return predictive regression is the kitchen sink regression including *pe*, V_{pe} and popular predictive variables used in Goyal and Welch (2008) with data available from 1937 to 2023.

In Panel A of Table 6, we report the results of the first set of multivariate predictive regressions of market excess return. When *pe* and V_{re} are predictors, *pe* continues to significantly predict negative market excess returns in each predictive horizon considered while V_{re} exhibits only weakly predictability in long-run, consistent with the results in the univariate regressions. When employing *pe* and V_{pe} as predictors, regardless of the predictive horizon, V_{pe} continues to significantly predict positive market excess return while *pe* significantly predicts market excess return with a negative sign except for the one-year horizon. The evidence of the positive predictive coefficient of V_{pe} and the negative predictive coefficient of *pe* is consistent with our second-order dynamic price-earning ratio model. This finding also suggests that pe and V_{pe} convey different information regarding return predictability. While many studies focus on valuation ratios (such as the price-earnings ratio) for predicting market returns, our finding highlights the role of volatility in the price-earnings ratio. This aligns with insights from Bansal et al. (2014) and Campbell et al. (2018), who demonstrate that stochastic volatility risk constitutes an independent risk beyond cash flow and discount rate risks. This perspective could add depth to current understandings of market return predictability by emphasizing that valuation and volatility factors contain distinct predictive information. Considering V_{re} and V_{pe} as predictors, V_{re} exhibits no predictability at all horizons. V_{pe} continues to significantly predict positive market excess return in each horizon, exhibiting superior predictive power than V_{re}. The result in Panel B of Table 6 is qualitatively similar when real return is employed as the dependent variable. Comparing three pairs of multivariate predictive regressions, we show that V_{pe} has superior predictive power compared to pe or V_{re}. The return predictability provided by the level and volatility of pe is distinct and cannot be fully explained by the other.[8]

We present the results of the kitchen sink regression in Table 7. Controlling price-earning ratio, dividend-price ratio, dividend yield, dividend payout ratio, relative T-bill rate, Book-to-Market ratio, default yield spread, long-term rate of returns, net equity expansion, inflation rate, percent equity issuing, stock variance, default return spread, term spread from Goyal and Welch (2008), V_{pe} continuously predicts positive future excess returns with statistic significance in all horizons. Overall, we find that the return predictability of V_{pe} can not be subsumed by existing predictors from the literature.

4.2 Out-of-sample return prediction

Goyal and Welch (2008) argue that the evidence of in-sample predictability should be considered cautiously and that it is important to test the out-of-sample (OOS) performance of return predictors. Taking into consideration the concerns regarding in-sample predictions, we adhere to their recommendation and proceed with the OOS test.

We employ the Clark and McCracken (2001) test to carry out the nested-model OOS forecasting analysis. Two restricted(benchmark) models commonly used in the literature (e.g., Lettau and

[8]We report the multivariate predictive regression results in quarterly frequency in Table B.2 and find similar results.

Ludvigson, 2001)are the constant mean model and the first-order autoregressive model, AR(1), respectively. The constant mean model has only one regressor, that is, the constant, and the AR(1) model includes two regressors, the constant, and the one-period lagged market excess returns or real returns. Given each restricted model, the corresponding unrestricted model includes one additional return predictor. Clark and McCracken (2001) provide two types of OOS tests: the equal forecast accuracy test and the forecast encompassing test. For the equal forecast accuracy test, the null hypothesis is that the restricted and unrestricted models have equal mean-squared forecasting errors (MSE), and the alternative is that the restricted model has a higher MSE. MSE-F provides the results of the equal forecast accuracy F test. For the encompassing test, the null hypothesis is that the restricted model forecast encompasses the unrestricted model, and the alternative is that the unrestricted model contains information that can significantly improve the restricted model's prediction. ENC-NEW provides the modified test statistics on forecast encompassing tests (e.g., Harvey et al., 1997).

The OOS-R^2 is measured as

$$OOS\ R^2 = 1 - (1 - \bar{R}^2)(\frac{T-1}{T-k-1}) \tag{12}$$

where $\bar{R}^2 = 1 - \frac{\sum_t (r_{t+n} - \hat{r}_{t+n|t})^2}{\sum_t (r_{t+n} - \bar{r}_t)^2}$, $\hat{r}_{t+n|t}$ is the return forecast based on an unrestricted model, and $\bar{r}_t$ is the historical average return for the constant mean model or return forecast based on AR(1) model. We choose the initial estimation period as from 1937 to 1966 (thirty years), and then recursively conduct the OOS forecasting test until 2023.[9]

Table 8 presents the ratio of mean-squared forecasting errors ($\frac{MSE_u}{MSE_r}$), MSE-F, ENC-NEW and OOS-R^2. We expect $\frac{MSE_u}{MSE_r}$ to be less than one, MSE-F and ENC-NEW to be statistically significant, and OOS-R^2 to be positive if a predictor exhibits *OOS* predictive power. In any case, whether employing constant mean model or AR(1) model as a benchmark model, using the dependent variable is market excess return or real return, we find that when the volatility of market returns (V_{re} or V_{rr}) as a predictor in an unrestricted model, the $\frac{MSE_u}{MSE_r}$ is always greater than one, suggesting that the mean-squared forecasting errors of the volatility of market returns-augmented model is always higher than that in any benchmark models. Both MSE-F and ENC-NEW tests

[9] For the robustness check, we also examine the OOS forecasting test using from 1937 to 1961 (twenty-five years) as the initial estimation period and obtain similar results.

cannot reject the null that the volatility of market returns contains no information about future excess returns or real returns, suggesting that the volatility of market returns cannot be used to improve upon the return predictability from the constant mean benchmark or AR(1) benchmark. The adjusted R^2 values are negative. This finding indicates that the volatility of market returns performs poorly in out-of-sample forecasts.

Regarding the *pe* ratio, OOS tests exhibit mixed results. The encompassing test rejects the null hypothesis that the restricted model forecast encompasses the unrestricted model based on ENC-NEW, suggesting the alternative that the *pe* contains information that can significantly improve the restricted model's prediction. In contrast, $\frac{MSE_u}{MSE_r}$ is greater than one, MSE-F test cannot be rejected and the OOS-R^2 is negative, suggesting poor out-of-sample forecast. The poor performance of volatility of market returns and *pe* is consistent with Goyal and Welch (2008) and Goyal et al. (2021).

With respect to the OOS forecast of V_{pe}, whether employing the constant mean model or AR(1) model as a benchmark model, forecasting excess returns or real returns, we find that the $\frac{MSE_u}{MSE_r}$ is always less than one, suggesting that the mean-squared forecasting errors of V_{pe}-augmented model is always lower compared to the one in a benchmark model. The MSE-F test strongly rejects the null of equal forecast accuracy between the benchmark model and V_{pe}-augmented model at the 5% significant level. The ENC-NEW test strongly rejects the null that the restricted model forecast encompasses V_{pe}-augmented model at the 5% significant level. The OOS-R^2s are always positive. For example, when predicting excess return, using the constant mean model as a restricted model and V_{pe}-augmented model as the unrestricted model, $\frac{MSE_u}{MSE_r}$ is 0.973, MSE-F test statistic is 2.331, ENC-NEW test statistic is 7.389, and OOS-R^2 is 0.027. When AR(1) model is used as a benchmark model, V_{pe} exhibits a better out-of-sample performance. $\frac{MSE_u}{MSE_r}$ is 0.946, MSE-F test statistic is 4.759, ENC-NEW test statistic is 11.757, and OOS-R^2 is 0.042. The results presented in Table 8 indicate that V_{pe} exhibits statistically significant out-of-sample predictive power for market excess returns and contains information that is not included in the constant mean model or AR(1) model. In addition, V_{pe} shows superior performance of OOS tests over *pe*, V_{re}. When predicting real returns, we find similar results.

A successful return predictor should be both statistically and economically significant. One can use the results reported in Table 8 to assess the economic value of predictability. Specifically, Campbell and Thompson (2008) have shown that the Sharpe ratio (SR^*) achieved by an active investor exploiting predictive information (i.e., predictive R^2) improves over the Sharpe ratio (SR) earned by a buy-and-hold investor. Specifically,

$$SR^* = \sqrt{\frac{SR^2 + OOS\ R^2}{1 - OOS\ R^2}} \tag{13}$$

Take the case in Panel B of Table 8 with $OOS\ R^2$ as 0.042. The annualized market Sharpe ratio (SR) for the period 1957–2023 is 0.412. Thus, the improved market Sharpe ratio $SR^* = \sqrt{\frac{0.412^2+0.042}{1-0.042}} = 0.471$. In other words, the buy-and-hold Sharpe ratio can be improved by 14.3 percent by leveraging predictive information. The proportional increase in the expected market returns from observing V_{pe}, ($\frac{OOS\ R^2}{1-OSS\ R^2}\frac{1+SR^2}{SR^2}$), is 30.2%. One can also compute the average utility gains of a mean-variance investor. For a mean-variance investor with a coefficient of relative risk aversion of three, the certainty equivalent return is 2.65%, which is higher than the 2% threshold discussed in Pástor and Stambaugh (2000).

To put it briefly, we present novel evidence from in-sample and OOS predictive tests, suggesting that V_{pe} significantly predicts positive future market excess return and real returns both statistically and economically, consistent with the prediction in leading asset pricing models with stochastic volatility (e.g., the habit model of Campbell and Cochrane (1999), long-run risk model of Bansal and Yaron (2004), and the rare disaster model of Barro (2006) and Gabaix (2012)) which anticipate a positive relationship between past realized volatility and future expected returns.

4.3 Predicting macroeconomic activities

Rational asset pricing literature exhibits that expected excess returns on common stocks are related to business conditions and vary countercyclically, indicating that risk premiums tend to be higher during economic recessions than in periods of expansion (e.g., Fama and French, 1989, Ferson and Harvey, 1991, Lettau and Ludvigson, 2001, and Cooper and Priestley, 2009). If the return predictability of V_{pe} reveals the rational response of investors to the business conditions, for example, cash flow news, time-varying investment opportunities, uncertainty, and risk aversion (e.g., Sundaresan, 1989, Campbell and Cochrane, 1999, Lettau and Ludvigson, 2001, and Bansal and Yaron, 2004), we expect that V_{pe}, based on our model, should predict lower future macroeconomic activities. Intuitively, high uncertainty of expected returns may reveal bad future states of economy. Fama and French (1993, 1995, 1996) argue that value factor, HML, and size factor, SMB, act as state variables in the context of Merton (1973) ICAPM, suggesting a risk-based explanation of value factor and size factor.[10] We posit that V_{pe} captures economic uncertainty related to business conditions if V_{pe} is a good candidate for a state variable within ICAPM and predicts macroeconomic growths, which are potential proxies for future investment opportunity set. We consider the following three macroeconomic activity series and obtain the data from U.S. Bureau of Economic Analysis: growth rate in Gross Domestic Product (GDP), growth rate in Personal Consumption Expenditures index (PCE), and growth rate in Corporate Net Cash Flow (NCF).

Panel A of Table 9 reports the univariate regression results showing that V_{pe} predicts all three measures of macroeconomic growth with a negative coefficient, consistent with the prediction in Equation (9) and a countercyclical nature of V_{pe}. In forecasting framework spanning from one year to ten years, V_{pe} exhibits a statistically significant predictability of GDP growth and PCE growth in one-year, three-year, five-year, seven-year, and ten-year horizons, while V_{pe} displays a statistically significant predictability of NCF growth in five-year, seven-year, and ten-year horizons. Our results suggest that high uncertainty of expected returns reveals low future macroeconomic activities and future bad states of the economy.

The literature has documented that Fama-French three factors contain information about future macroeconomic growth (e.g., Fama, 1981, and Liew and Vassalou, 2000). To examine whether the predictive power of V_{pe} for future macroeconomic activities is subsumed by Fama-French three factors, we run the macroeconomic growth predictive regressions of V_{pe} including Fama-French three factors. To save space, we report only the predictive coefficients and statistics of V_{pe} and adjusted R^2 in Panel B of Table 9. The detailed results are reported in Table B.3. Controlling for Fama-French three factors, V_{pe} exhibits a similar pattern of predictability of macroeconomic growth, suggesting that the negative relationship between V_{pe} and future macroeconomic growth is not subsumed by known relation between Fama-French three factors and future macroeconomic growth.

[10] Empirically Liew and Vassalou (2000) and Vassalou (2003) show that HML and SMB contain information on future economic growth.

4.4 Predicting market volatility

Our model posits that V_{pe}, the volatility of the log price-earnings ratio, serves as a predictor not only for positive future market returns and negative future economic growth but also for a decline in long-term market volatility. To test this, we examine three measures of market volatility: the volatility of market excess returns (V_{re}), the volatility of market real returns(V_{rr}), and the conditional volatility of market returns(V_m) based on the vector autoregressive (VAR) model following Bansal et al. (2014).

Table 10 presents the predictive regression results using V_{pe} as an independent variable across different time horizons for each volatility measure. For the volatility of realized returns (V_{re} V_{rr}), V_{pe} is associated with an increase in future market volatility at the one-year horizon. However, over longer horizons of seven and ten years, V_{pe} forecasts a decrease in market volatility. In addition, V_{pe} forecasts a negative, albeit statistically weak, relationship with V_m across all horizons from one to ten years. Notably, the finding that V_{pe} predicts a decline in both realized and conditional market volatility over longer horizons aligns with Andersen et al. (2003), who demonstrate that long-term averages of realized volatility tend to converge with forecasted (conditional) volatility as more data becomes available. Overall, our results suggest that V_{pe} serves as a meaningful predictor of long-run market volatility, with a negative coefficient, aligning with the implications of our second-order dynamic price-earnings ratio model. In addition, Adrian and Rosenberg (2008) find that the long-run volatility component aligns closely with macroeconomic conditions, especially business cycle fluctuations. One plausible explanation of the superior predictive power of V_{pe} is that it effectively captures the long-run volatility component.

In sum, we present novel empirical results that V_{pe} predicts high future market returns, low future macroeconomic growth, and a decline in long-run market volatility. These findings align with our second-order dynamic price-earnings ratio model and support the positive risk-return trade-off theory and the relationship between time-varying returns and business conditions.[11] Importantly, V_{pe} significantly predicts market returns both statistically and economically, outperforming pe, V_{re}, and V_{rr} in return predictability, while remaining robust against other established predictors in the literature.

[11] We obtain similar findings with quarterly data. The results are available upon request.

5 Sources of return predictability

In asset pricing literature, a key debate centers around the origins of the risk premium—specifically, whether it arises primarily from time-varying risk aversion or long-run economic risks. For example, Bansal and Yaron (2004) focus on the importance of long-run risk in consumption growth for explaining the equity premium and the dynamic dependencies in returns over long multi-year horizons, highlighting the role of cash flow risk. On the other hand, the habit-formation model by Campbell and Cochrane (1999) emphasizes time-varying discount rates driven by changing risk aversion.

To gain a deeper understanding of the superior and significant predictive relation between V_{pe} and future market returns, macroeconomic activities, as well as market volatility, we conduct additional predictive analysis of V_{pe} to investigate whether the predictability of V_{pe} arises from cash flow shocks, discount rate shocks, or volatility shocks (e.g., Bansal et al., 2014; Campbell et al., 2018). Additionally, we explore whether these factors can be further associated with the price of risk or the quantity of risk (e.g., Bao et al., 2023).

We consider k-year ahead Gross Domestic Product growth (G_{GDP}), Personal Consumption Expenditures index growth (G_{PCE}), and Corporate Net Cash Flow growth (G_{NCF}) as proxies for future cash flow shocks. We proxy future discount rate shocks using k-year-ahead dividend-price ratio (dp), term spread (tms), and default spread (dfr). The k-year-ahead volatility of market excess returns (V_{re}), the volatility of Gross Domestic Product growth (V_{GDP}), the volatility of Personal Consumption Expenditures index growth (V_{PCE}) and the volatility of Corporate Net Cash Flow growth (V_{NCF}) are used as proxies for future volatility shocks. The k-year-ahead shocks directly correspond to the k-year-ahead forecast regression.

Table 11 presents the results of multivariate predictive regressions with controls. For comparison, we also report the univariate regression results since the data sample lengths of controls vary in each panel. The univariate regression results in each panel once again highlight the robust and significant predictive power of V_{pe} for future excess returns across horizons from one to ten years ahead, with significance levels of at least 5%. In Panel A of Table 11, we examine the predictive power of V_{pe} for k-year-ahead future excess returns controlling for k-year-ahead future cash flow shocks. V_{pe} continuously predicts future returns for all horizons considered after controlling for future cash flow shocks. For instance, after controlling for cash flow shocks, a one percent increase in V_{pe} significantly predicts the future excess returns of 0.657%, 1.408%, 2.528%, 3.191% and 4.954% over the one-year, three-year, five-year, seven-year, and ten-year horizons, respectively. The adjusted R^2 values for these horizons are 2.2%, 22.2%, 34.4%, 38.2% and 39.4%. Compared to the univariate forecast coefficients, the multivariate regression coefficients decrease sizably (by 20 - 30%) and the multivariate regression adjusted R^2s increase by 23% to 48%, except for the one-year-ahead forecast. The findings indicate that the predictive power of V_{pe} is indeed associated with future cash flow shocks, particularly in long-run.

Penal B of Table 11 presents results when we control for future discount rate shocks. V_{pe} continuously predicts future excess returns for all horizons considered after controlling for discount rate shocks. The predictive coefficients of V_{pe} decrease sizably (by 10 - 22%) and the adjusted R^2s improve substantially, increasing by 50% to 85%, after controlling for discount rate shocks. For example, the predictive coefficients of V_{pe} for one-year, three-year, five-year, seven-year, and ten-year ahead horizons are 0.522, 1.692, 2.875, 3.919 and 6.711, respectively, after controlling for discount rate shocks, compared to 0.605, 1.874, 3.319, 4.823 and 8.570 in univariate forecast regressions. The adjusted R^2 are 9.4%, 27.7%, 47.3%, 54.4% and 56%. Our results suggest that the return predictability of V_{pe} is partially attributable to the correlation between V_{pe} and future discount rate shocks.

The return predictability may also arise because V_{pe} signals periods of changing risk and uncertainty in the economy and market. In essence, investors typically request higher risk premium when they perceive a greater level of risk. We examine the return predictability of V_{pe} controlling for future volatility shocks in Panel C of Table 11. V_{pe} continuously predicts future returns for all horizons considered after controlling for volatility shocks. The predictive coefficients, however, change moderately, suggesting the impact of future volatility shocks is relatively small. This result is consistent with the evidence of weaker market volatility predictive power of V_{pe} in previous section. The findings indicate that the return predictive power of V_{pe} can be moderately accounted for by its relationship with volatility shocks.

In the above analysis, by controlling for each type of shocks individually, the return predictability of V_{pe} remains significant although the predictive coefficients are affected by those shocks. Next, we examine the return predictability of V_{pe} by controlling all three types of shocks simultaneously.

Penal D of Table 11 displays the results. The predictive power of V_{pe} remains strong and significant for one-year, three-year, five-year, and seven-year horizons, but becomes weak and insignificant at ten-year horizon. The predictive coefficients of V_{pe} in multivariate regressions experience a substantial decrease in medium and long-run, and the adjusted R^2s increase remarkably. For example, when controlling for all shocks, the predictive coefficients of V_{pe} are 0.685, 1.278, 2.555, 2.178, and 1.787 for one-year, three-year, five-year, seven-year, and ten-year horizons, respectively, compared to 0.573, 1.755, 3.262, 4.545, and 7.222 in the univariate regressions, respectively. It is worth noting that the predictive coefficient of V_{pe} in the ten-year horizon decreases substantially from 7.222 to 1.787 and also becomes insignificant. Additionally, the adjusted R^2s are 10.0%, 40.9%, 65.6%, 74.7%, and 70.5% for one-year, three-year, five-year, seven-year, and ten-year ahead horizons, respectively, compared to 4.7%, 18.0%, 25.6%, 25.8%, and 28.9% in univariate regressions, respectively.

Our results in Table 11 indicate that future cash flow shocks, discount rate shocks and volatility shocks are closely related to the return predictability of V_{pe}. For shorter horizons (one-year, three-year, five-year, and seven-year), the predictive coefficients of V_{pe} remain significant after controlling for all shocks, suggesting that its return predictability cannot be fully explained by the quantity of risk but also reflects the price of risk. On the other hand, for the ten-year horizon, the predictability of V_{pe} is entirely explained by these three shocks, suggesting that at longer horizon, the return predictability mainly reflects the quantity of risk.

6 Conclusion

In this study, we propose a second-order dynamic price-earnings ratio model that highlights the importance of the log price-earnings ratio's second moment in understanding return dynamics and forecasting economic conditions. Our findings reveal that the level and volatility of the price-earnings ratio provide powerful forecasts of future market returns, cash flow growth, and market volatility, capturing significant time variation in the expected market risk premium and broader macroeconomic activity.

Our evidence underscores the unique predictive strength of the volatility of the price-earnings ratio, both statistically and economically, outperforming both the level of the price-earnings ratio and traditional measures of market volatility as return predictors. This predictive power holds consistently across different sample periods, frequencies, and controls, underscoring the robustness of our model both in-sample and out-of-sample. We show that the predictive role of price-earnings ratio volatility varies by investment horizon. Below ten-year horizon, return predictability cannot be fully attributed to risks associated with cash flow, discount rates, and volatility; rather, it also reflects the price of risk, indicating a more complex interaction of risk factors. At longer horizons, however, the predictability becomes primarily driven by quantities of risk, specifically cash flow, discount rate, and volatility shocks. Overall, our model introduces a new dimension to understanding the role of price-earnings volatility in asset pricing and return forecasting,

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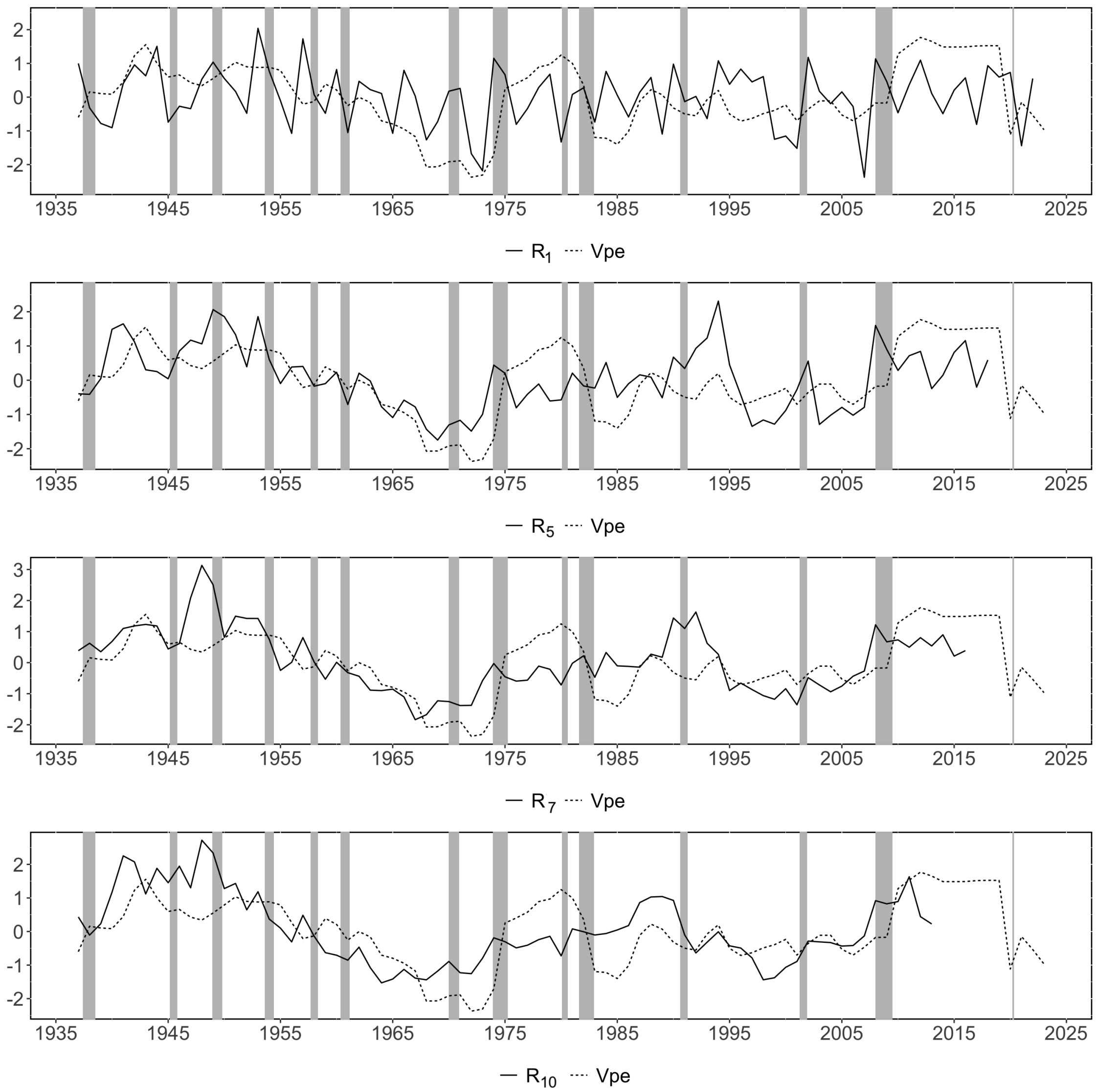

Figure 1: Volatility of log price-earnings ratio and subsequent market excess returns. The figure plots the time series of the volatility of log price-earnings ratio (dashed line) and subsequent compounded one-year (R_1), five-year (R_5), seven-year (R_7) and ten-year (R_{10}) market excess returns (solid line), normalized to have zero mean and unit standard deviation. The shaded areas represent NBER recession dates.

Table 1: Descriptive statistics

This table reports summary statistics and unit-root test for market excess returns (R_e), market real returns (R_r), log price-earnings ratio (pe) from $S\&P$ 500 index, the volatility of market excess returns (V_{re}), the volatility of market real returns (V_{rr}) and the volatility of log price-earnings ratio (V_{pe}). ρ is the first-order autocorrelation coefficient. ADF and PP denote the augmented Dickey-Fuller test and the Philips-Perron test with four lags. The critical values for ADF and PP are -3.453, -2.871, and -2.572 at 1%, 5%, and 10% significance levels, respectively. The sample period is from 1937 to 2023.

Panel A: Summary statistics and unit-root test						
Series	Mean	Std	ρ	ADF	PP	
R_e	0.085	0.203	-0.009	-6.102	-9.825	
R_r	0.086	0.199	-0.031	-5.776	-10.175	
pe	2.775	0.407	0.776	-2.484	-4.077	
V_{re}	0.191	0.055	0.889	-3.927	-2.773	
V_{rr}	0.189	0.051	0.890	-3.409	-2.625	
V_{pe}	0.264	0.074	0.853	-3.039	-3.130	
Panel B: Correlation matrix						
	R_e	R_r	pe	V_{re}	V_{rr}	V_{pe}
R_e	1.000	0.983	0.170	-0.034	0.010	0.250
R_r		1.000	0.191	-0.084	-0.051	0.182
pe			1.000	-0.305	-0.364	-0.211
V_{re}				1.000	0.975	0.318
V_{rr}					1.000	0.369
V_{pe}						1.000

Table 2: Univariate predictive regressions for market returns (1937-2023)

This table reports univariate long-horizon predictive regressions for compounded market excess returns (R_e) and real returns (R_r) at horizons of k = 1, 3, 5, 7, and 10 years ahead. The predictive variables are the log price-earnings ratio of $S\&P$ 500 index (pe), the volatility of market excess returns (V_{re}), the volatility of market real returns (V_{rr}), and the volatility of log price-earnings ratio (V_{pe}). The table reports estimates of OLS regression, Newey and West (1987) corrected standard errors (with k+1 lags) in parentheses, Hodrick (1992) standard errors (with k lags) in brackets, bootstrapping p-value in curly brackets and adjusted R-squared in the bottom line of each prediction horizon. The annual sample period is from 1937 to 2023.

	$R_{e,t+k}$			$R_{r,t+k}$		
k	pe	V_{re}	V_{pe}	pe	V_{rr}	V_{pe}
1	-0.081	0.019	0.605	-0.078	-0.094	0.493
	(0.039)	(0.338)	(0.213)	(0.037)	(0.383)	(0.221)
	[0.044]	[0.327]	[0.298]	[0.042]	[0.374]	[0.287]
	{0.070}	{0.911}	{0.014}	{0.085}	{0.802}	{0.045}
	0.026	-0.012	0.053	0.024	-0.011	0.032
3	-0.234	0.206	1.874	-0.229	-0.322	1.492
	(0.107)	(0.909)	(0.439)	(0.083)	(0.865)	(0.453)
	[0.113]	[0.906]	[0.811]	[0.105]	[1.037]	[0.792]
	{0.006}	{0.721}	{0.000}	{0.005}	{0.641}	{0.003}
	0.086	-0.011	0.184	0.084	-0.009	0.114
5	-0.356	1.118	3.319	-0.338	-0.505	2.714
	(0.211)	(1.295)	(0.795)	(0.174)	(1.305)	(0.871)
	[0.187]	[1.397]	[1.282]	[0.182]	[1.523]	[1.262]
	{0.003}	{0.267}	{0.000}	{0.004}	{0.604}	{0.000}
	0.086	0.004	0.259	0.082	-0.009	0.180
7	-0.610	2.274	4.823	-0.616	-0.284	4.064
	(0.338)	(1.562)	(1.260)	(0.275)	(1.842)	(1.243)
	[0.253]	[1.751]	[1.631]	[0.247]	[2.046]	[1.606]
	{0.001}	{0.084}	{0.000}	{0.001}	{0.777}	{0.000}
	0.147	0.027	0.294	0.161	-0.012	0.218
10	-1.170	5.631	8.570	-1.212	0.663	7.318
	(0.548)	(2.383)	(2.430)	(0.375)	(3.072)	(1.801)
	[0.338]	[1.703]	[2.002]	[0.326]	[2.053]	[1.959]
	{0.001}	{0.007}	{0.000}	{0.001}	{0.686}	{0.000}
	0.211	0.082	0.333	0.280	-0.012	0.293

Table 3: Univariate predictive regressions for market returns (quarterly)

This table reports univariate long-horizon predictive regressions for compounded market excess returns (R_e) and real returns (R_r), at horizons of k = 1, 2, 3, 4, 12, 20, 28 and 40 quarters ahead. The predictive variables are the log price-earnings ratio of $S\&P$ 500 index (pe), the volatility of market excess returns (V_{re}), the volatility of market real returns (V_{rr}), and the volatility of log price-earnings ratio (V_{pe}). The table reports estimates of OLS regression, Newey and West (1987) corrected standard errors (with k+1 lags) in parentheses, Hodrick (1992) standard errors (with k lags) in brackets, bootstrapping p-value in curly brackets and adjusted R-squared in the bottom line of each prediction horizon. The sample period is from 1937:Q1 to 2023:Q4.

	$R_{e,t+k}$			$R_{r,t+k}$		
k	pe	V_{re}	V_{pe}	pe	V_{rr}	V_{pe}
1	-0.010	-0.068	0.087	-0.007	-0.124	0.070
	(0.014)	(0.156)	(0.039)	(0.014)	(0.161)	(0.039)
	[0.012]	[0.156]	[0.041]	[0.012]	[0.159]	[0.041]
	{0.335}	{0.604}	{0.043}	{0.528}	{0.254}	{0.082}
	0.000	-0.002	0.008	-0.002	0.001	0.004
2	-0.024	-0.108	0.161	-0.019	-0.220	0.128
	(0.027)	(0.259)	(0.070)	(0.026)	(0.262)	(0.071)
	[0.024]	[0.306]	[0.082]	[0.024]	[0.312]	[0.082]
	{0.131}	{0.505}	{0.013}	{0.234}	{0.162}	{0.045}
	0.004	-0.002	0.015	0.001	0.002	0.008
3	-0.042	-0.127	0.232	-0.036	-0.300	0.183
	(0.036)	(0.343)	(0.102)	(0.035)	(0.336)	(0.103)
	[0.034]	[0.452]	[0.122]	[0.034]	[0.459]	[0.122]
	{0.043}	{0.520}	{0.011}	{0.072}	{0.164}	{0.022}
	0.011	-0.002	0.021	0.007	0.003	0.011
4	-0.060	-0.123	0.313	-0.055	-0.362	0.249
	(0.043)	(0.414)	(0.134)	(0.042)	(0.387)	(0.136)
	[0.043]	[0.567]	[0.163]	[0.043]	[0.575]	[0.163]
	{0.004}	{0.598}	{0.003}	{0.015}	{0.157}	{0.009}
	0.019	-0.002	0.031	0.015	0.004	0.017
12	-0.189	0.486	1.187	-0.186	-0.502	1.002
	(0.111)	(1.272)	(0.318)	(0.093)	(1.021)	(0.341)
	[0.105]	[1.105]	[0.478]	[0.104]	[1.125]	[0.477]
	{0.001}	{0.208}	{0.000}	{0.001}	{0.286}	{0.000}
	0.069	0.002	0.158	0.063	0.002	0.106
20	-0.286	2.034	2.086	-0.284	-0.504	1.735
	(0.223)	(1.537)	(0.611)	(0.192)	(1.150)	(0.679)
	[0.153]	[1.508]	[0.694]	[0.153]	[1.494]	[0.693]
	{0.001}	{0.000}	{0.000}	{0.001}	{0.394}	{0.000}
	0.069	0.033	0.219	0.067	-0.001	0.147
28	-0.512	3.710	3.260	-0.529	-0.473	2.830
	(0.340)	(1.593)	(1.013)	(0.301)	(1.565)	(1.182)
	[0.201]	[1.537]	[0.893]	[0.201]	[1.618]	[0.891]
	{0.001}	{0.000}	{0.000}	{0.001}	{0.552}	{0.000}
	0.125	0.064	0.266	0.133	-0.002	0.199
40	-0.931	8.331	6.384	-1.005	0.535	5.704
	(0.560)	(3.211)	(1.763)	(0.437)	(3.283)	(2.093)
	[0.274]	[1.689]	[1.283]	[0.275]	[1.807]	[1.281]
	{0.001}	{0.000}	{0.000}	{0.001}	{0.615}	{0.000}
	0.167	0.137	0.325	0.232	-0.003	0.307

Table 4: Univariate predictive regressions for market returns (subsamples)

This table reports univariate long-horizon predictive regressions for compounded market excess returns (R_e) and real returns (R_r), at horizons of $k = 1, 3, 5, 7$ and 10 years ahead. The predictive variables are the log price-earnings ratio of $S\&P$ 500 index (pe), the volatility of market excess returns (V_{re}), the volatility of market real returns (V_{rr}), and the volatility of log price-earnings ratio (V_{pe}). The table reports estimates of OLS regression, Newey and West (1987) corrected standard errors (with k+1 lags) in parentheses, Hodrick (1992) standard errors (with k lags) in brackets, bootstrapping p-value in curly brackets and adjusted R-squared in the bottom line of each prediction horizon. The annual sample periods span from 1937 to 1999, from 1937 to 2007, from 1937 to 2019, and from 1950 to 2023, respectively.

Panel A: Excess returns												
	1937-1999			1937-2007			1937-2019			1950-2023		
k	pe	V_{re}	V_{pe}	pe	V_{re}	V_{pe}	pe	V_{re}	V_{pe}	pe	V_{re}	V_{pe}
1	-0.113	-0.127	0.687	-0.120	0.010	0.732	-0.089	0.040	0.633	-0.060	0.032	0.555
	(0.053)	(0.352)	(0.288)	(0.045)	(0.364)	(0.275)	(0.041)	(0.364)	(0.220)	(0.042)	(0.520)	(0.216)
	[0.053]	[0.344]	[0.398]	[0.054]	[0.342]	[0.389]	[0.045]	[0.341]	[0.309]	[0.051]	[0.573]	[0.306]
	{0.074}	{0.708}	{0.016}	{0.019}	{0.990}	{0.025}	{0.043}	{0.884}	{0.013}	{0.216}	{0.990}	{0.026}
	0.040	-0.015	0.067	0.064	-0.015	0.069	0.033	-0.012	0.059	0.005	-0.014	0.044
3	-0.342	-0.344	1.947	-0.321	0.023	2.026	-0.262	0.121	1.879	-0.125	-0.122	1.656
	(0.195)	(0.976)	(0.642)	(0.130)	(0.944)	(0.614)	(0.113)	(0.942)	(0.490)	(0.100)	(1.493)	(0.429)
	[0.154]	[0.945]	[1.075]	[0.143]	[0.937]	[1.060]	[0.120]	[0.937]	[0.861]	[0.128]	[1.583]	[0.828]
	{0.001}	{0.635}	{0.000}	{0.001}	{0.985}	{0.000}	{0.003}	{0.848}	{0.000}	{0.129}	{0.889}	{0.000}
	0.118	-0.013	0.182	0.150	-0.015	0.172	0.106	-0.012	0.175	0.015	-0.014	0.174
5	-0.535	0.481	3.676	-0.513	1.016	3.821	-0.409	1.078	3.424	-0.194	-0.269	3.074
	(0.355)	(1.496)	(1.112)	(0.228)	(1.289)	(1.086)	(0.215)	(1.309)	(0.902)	(0.204)	(2.551)	(0.769)
	[0.244]	[1.388]	[1.656]	[0.228]	[1.389]	[1.620]	[0.194]	[1.392]	[1.365]	[0.186]	[2.596]	[1.276]
	{0.007}	{0.653}	{0.000}	{0.001}	{0.301}	{0.000}	{0.005}	{0.290}	{0.000}	{0.189}	{0.809}	{0.000}
	0.126	-0.014	0.305	0.170	0.001	0.295	0.114	0.003	0.251	0.015	-0.015	0.254
7	-0.873	1.275	5.048	-0.861	1.976	5.307	-0.661	2.238	5.180	-0.300	-0.662	4.046
	(0.525)	(1.901)	(1.665)	(0.394)	(1.551)	(1.654)	(0.337)	(1.575)	(1.433)	(0.268)	(3.443)	(1.068)
	[0.328]	[1.712]	[2.040]	[0.278]	[1.680]	[2.011]	[0.262]	[1.740]	[1.804]	[0.252]	[3.075]	[1.606]
	{0.003}	{0.418}	{0.000}	{0.001}	{0.162}	{0.000}	{0.001}	{0.067}	{0.000}	{0.082}	{0.786}	{0.000}
	0.167	-0.005	0.294	0.221	0.017	0.299	0.170	0.025	0.298	0.034	-0.014	0.297
10	-1.894	4.139	8.676	-1.692	4.380	8.791	-1.191	5.260	9.101	-0.663	0.614	6.393
	(0.724)	(2.990)	(2.830)	(0.662)	(2.430)	(2.890)	(0.546)	(2.448)	(3.055)	(0.417)	(5.663)	(1.704)
	[0.450]	[1.560]	[2.311]	[0.354]	[1.355]	[2.282]	[0.333]	[1.666]	[2.304]	[0.327]	[3.520]	[1.828]
	{0.001}	{0.112}	{0.000}	{0.001}	{0.035}	{0.000}	{0.001}	{0.006}	{0.000}	{0.003}	{0.858}	{0.000}
	0.279	0.032	0.335	0.283	0.047	0.337	0.228	0.071	0.327	0.098	-0.016	0.317

Panel B: Real returns

	1937-1999			1937-2007			1937-2019			1950-2021		
k	pe	V_{rr}	V_{pe}	pe	V_{rr}	V_{pe}	pe	V_{rr}	V_{pe}	pe	V_{rr}	V_{pe}
1	-0.091	-0.270	0.554	-0.104	-0.126	0.598	-0.080	-0.110	0.504	-0.069	0.129	0.497
	(0.055)	(0.412)	(0.306)	(0.044)	(0.417)	(0.290)	(0.039)	(0.414)	(0.232)	(0.040)	(0.523)	(0.229)
	[0.051]	[0.401]	[0.387]	[0.051]	[0.396]	[0.378]	[0.043]	[0.393]	[0.300]	[0.048]	[0.575]	[0.297]
	{0.143}	{0.490}	{0.079}	{0.060}	{0.773}	{0.052}	{0.091}	{0.799}	{0.053}	{0.196}	{0.879}	{0.050}
	0.019	-0.009	0.036	0.044	-0.013	0.040	0.024	-0.011	0.033	0.012	-0.014	0.034
3	-0.281	-0.942	1.589	-0.279	-0.539	1.664	-0.243	-0.487	1.512	-0.181	0.353	1.500
	(0.182)	(0.920)	(0.658)	(0.108)	(0.880)	(0.607)	(0.089)	(0.882)	(0.498)	(0.090)	(1.501)	(0.476)
	[0.145]	[1.105]	[1.064]	[0.133]	[1.085]	[1.050]	[0.112]	[1.081]	[0.844]	[0.121]	[1.579]	[0.804]
	{0.039}	{0.219}	{0.005}	{0.003}	{0.508}	{0.004}	{0.004}	{0.456}	{0.003}	{0.057}	{0.760}	{0.000}
	0.070	0.010	0.111	0.108	-0.007	0.109	0.090	-0.007	0.110	0.047	-0.013	0.137
5	-0.433	-1.101	3.238	-0.433	-0.497	3.344	-0.371	-0.504	2.912	-0.309	0.380	2.918
	(0.345)	(1.507)	(1.170)	(0.204)	(1.299)	(1.108)	(0.180)	(1.303)	(0.940)	(0.180)	(2.868)	(0.889)
	[0.238]	[1.518]	[1.650]	[0.222]	[1.510]	[1.614]	[0.189]	[1.518]	[1.352]	[0.176]	[2.715]	[1.242]
	{0.015}	{0.323}	{0.000}	{0.004}	{0.732}	{0.000}	{0.006}	{0.643}	{0.000}	{0.023}	{0.779}	{0.000}
	0.078	0.000	0.235	0.119	-0.012	0.227	0.097	-0.010	0.188	0.057	-0.014	0.217
7	-0.814	-1.266	4.529	-0.771	-0.512	4.777	-0.645	-0.284	4.581	-0.505	-0.193	4.060
	(0.497)	(2.128)	(1.533)	(0.361)	(1.792)	(1.422)	(0.279)	(1.842)	(1.250)	(0.227)	(3.823)	(1.191)
	[0.320]	[1.984]	[2.029]	[0.272]	[1.975]	[2.000]	[0.255]	[2.037]	[1.787]	[0.239]	[3.264]	[1.567]
	{0.003}	{0.482}	{0.000}	{0.001}	{0.699}	{0.000}	{0.001}	{0.822}	{0.000}	{0.001}	{0.897}	{0.000}
	0.150	-0.007	0.244	0.182	-0.014	0.249	0.170	-0.013	0.243	0.110	-0.015	0.263
10	-1.912	-1.048	7.860	-1.587	-0.747	7.878	-1.222	0.463	8.273	-1.076	0.317	6.746
	(0.511)	(3.841)	(1.947)	(0.501)	(2.854)	(1.902)	(0.377)	(3.008)	(1.926)	(0.344)	(6.146)	(1.591)
	[0.438]	[1.806]	[2.273]	[0.350]	[1.737]	[2.244]	[0.321]	[2.029]	[2.265]	[0.314]	[3.892]	[1.792]
	{0.001}	{0.659}	{0.000}	{0.001}	{0.723}	{0.000}	{0.001}	{0.803}	{0.000}	{0.003}	{0.957}	{0.000}
	0.355	-0.016	0.338	0.304	-0.015	0.329	0.288	-0.013	0.321	0.241	-0.016	0.300

Table 5: Univariate predictive regressions for $S\&P$ 500 index real returns (1881-2023)

This table reports univariate long-horizon predictive regressions for compounded $S\&P$ 500 index real returns (R_r) at horizons of $k = 1$, 3, 5, 7 and 10 years ahead. The predictive variables are the log price-earnings ratio of $S\&P$ 500 index (pe), the volatility of $S\&P$ 500 index real returns (V_{rr}), and the volatility of log price-earnings ratio (V_{pe}). The table reports estimates of OLS regression, Newey and West (1987) corrected standard errors (with k+1 lags) in parentheses, Hodrick (1992) standard errors(with k lags) in brackets, bootstrapping p-value in curly brackets and adjusted R-squared in the bottom line of each prediction horizon. The annual sample period is from 1881 to 2023.

	$R_{r,t+k}$		
k	pe	V_{rr}	V_{pe}
1	-0.019	-0.078	0.400
	(0.037)	(0.327)	(0.140)
	[0.035]	[0.355]	[0.169]
	{0.687}	{0.780}	{0.033}
	-0.005	-0.007	0.030
3	-0.061	-0.343	1.231
	(0.096)	(0.806)	(0.338)
	[0.091]	[0.995]	[0.473]
	{0.390}	{0.521}	{0.000}
	-0.002	-0.005	0.108
5	-0.120	-0.938	2.198
	(0.161)	(1.131)	(0.575)
	[0.152]	[1.595]	[0.747]
	{0.262}	{0.258}	{0.000}
	0.002	0.002	0.166
7	-0.204	-1.481	3.039
	(0.216)	(1.390)	(0.771)
	[0.203]	[2.077]	[1.009]
	{0.121}	{0.153}	{0.000}
	0.011	0.008	0.203
10	-0.531	-0.828	4.287
	(0.265)	(2.131)	(1.022)
	[0.276]	[2.714]	[1.431]
	{0.001}	{0.554}	{0.000}
	0.072	-0.005	0.251

Table 6: Multivariate predictive regressions for market returns(1937-2021)

This table reports multivariate long-horizon predictive regressions for compounded market excess returns and real returns at horizons of $k = 1$, 3, 5, 7 and 10 years ahead. We consider three pairs of predictive variables, the log price-earnings ratio of $S\&P$ 500 index (pe) and the volatility of market excess returns (V_{re}) or the volatility of market real returns (V_{rr}), the log price-earnings ratio of $S\&P$ 500 index (pe) and the volatility of log price-earnings ratio (V_{pe}), and the volatility of market returns (V_{re} or V_{rr}) and the volatility of log price-earnings ratio (V_{pe}), respectively. The table reports estimates of OLS regression, Newey and West (1987) corrected standard errors (with k+1 lags) in parentheses, Hodrick (1992) standard errors (with k lags) in brackets, bootstrapping p-value in curly brackets and adjusted R-squared (R^2) of each prediction horizon. The sample period is from 1937 to 2023.

Panel A: Excess returns									
k	pe	V_{re}	R^2	pe	V_{pe}	R^2	V_{re}	V_{pe}	R^2
1	-0.088	-0.185	0.017	-0.062	0.533	0.063	-0.262	0.666	0.048
	(0.040)	(0.326)		(0.039)	(0.213)		(0.299)	(0.222)	
	[0.049]	[0.601]		[0.051]	[0.292]		[0.628]	[0.313]	
	{0.053}	{0.581}		{0.177}	{0.046}		{0.453}	{0.019}	
3	-0.246	-0.330	0.078	-0.176	1.678	0.228	-0.649	2.022	0.186
	(0.112)	(0.843)		(0.097)	(0.383)		(0.743)	(0.451)	
	[0.139]	[1.751]		[0.141]	[0.742]		[1.804]	[0.781]	
	{0.009}	{0.616}		{0.023}	{0.003}		{0.265}	{0.000}	
5	-0.340	0.466	0.077	-0.249	3.044	0.296	-0.389	3.413	0.251
	(0.223)	(1.294)		(0.180)	(0.650)		(1.282)	(0.872)	
	[0.210]	[1.994]		[0.216]	[1.139]		[2.050]	[1.135]	
	{0.013}	{0.641}		{0.022}	{0.000}		{0.657}	{0.000}	
7	-0.570	1.164	0.146	-0.431	4.227	0.361	0.211	4.770	0.285
	(0.362)	(1.564)		(0.280)	(0.918)		(1.597)	(1.325)	
	[0.263]	[2.052]		[0.255]	[1.102]		[2.020]	[1.101]	
	{0.001}	{0.324}		{0.001}	{0.000}		{0.923}	{0.000}	
10	-1.040	3.562	0.236	-0.790	7.098	0.417	2.272	7.959	0.338
	(0.566)	(2.386)		(0.435)	(1.686)		(1.995)	(2.285)	
	[0.348]	[2.300]		[0.351]	[1.440]		[2.306]	[1.422]	
	{0.001}	{0.057}		{0.004}	{0.000}		{0.216}	{0.000}	

Panel B: Real returns									
k	pe	V_{rr}	R^2	pe	V_{pe}	R^2	V_{rr}	V_{pe}	R^2
1	-0.094	-0.376	0.023	-0.063	0.421	0.043	-0.410	0.597	0.033
	(0.039)	(0.390)		(0.037)	(0.228)		(0.371)	(0.242)	
	[0.049]	[0.579]		[0.049]	[0.285]		[0.610]	[0.313]	
	{0.049}	{0.331}		{0.171}	{0.099}		{0.297}	{0.029}	
3	-0.275	-1.105	0.101	-0.185	1.286	0.164	-1.288	1.809	0.142
	(0.095)	(0.865)		(0.075)	(0.437)		(0.736)	(0.512)	
	[0.141]	[1.669]		[0.139]	[0.722]		[1.712]	[0.770]	
	{0.001}	{0.108}		{0.008}	{0.007}		{0.041}	{0.000}	
5	-0.395	-1.521	0.096	-0.252	2.435	0.221	-2.390	3.338	0.230
	(0.187)	(1.402)		(0.152)	(0.804)		(1.125)	(0.983)	
	[0.210]	[2.075]		[0.212]	[1.121]		[2.149]	[1.151]	
	{0.001}	{0.157}		{0.016}	{0.000}		{0.018}	{0.000}	
7	-0.697	-2.077	0.177	-0.472	3.411	0.305	-3.051	4.907	0.263
	(0.290)	(1.826)		(0.237)	(1.097)		(1.390)	(1.356)	
	[0.269]	[2.252]		[0.255]	[1.104]		[2.211]	[1.113]	
	{0.001}	{0.111}		{0.007}	{0.000}		{0.018}	{0.000}	
10	-1.321	-2.730	0.291	-0.911	5.620	0.435	-4.206	8.604	0.330
	(0.433)	(3.088)		(0.293)	(1.491)		(2.095)	(1.882)	
	[0.357]	[2.746]		[0.353]	[1.439]		[2.750]	[1.425]	
	{0.001}	{0.127}		{0.001}	{0.000}		{0.017}	{0.000}	

Table 7: Kitchen sink regression

This table reports the estimates from kitchen sink long-horizon predictive regressions for compounded market excess returns at horizons of $k = 1, 3, 5, 7$ and 10 years ahead. The predictive variables are the volatility of log price-earnings ratio (V_{pe}), the log price-earning ratio (pe), and predictors in Goyal and Welch (2008) available in the sample from 1937 to 2023, including the dividend-price ratio (dp), the dividend yield (dy), the dividend payout ratio (de), the relative T-bill rate (rtb), the Book-to-Market ratio (bm), default yield spread (dfy), the long term rate of returns (ltr), net equity expansion ($ntis$), the inflation rate ($infl$), percent equity issuing ($eqis$), stock variance ($svar$), default return spread (dfr), and term spread (tms). The table reports estimates of OLS regression, Newey and West (1987) corrected standard errors (with k+1 lags) in parentheses, Hodrick (1992) standard errors (with k lags) in brackets, bootstrapping p-value in curly brackets and adjusted R-squared (R^2) of each prediction horizon. The sample period is from 1937 to 2023.

k	V_{pe}	pe	dp	dy	de	rtb	bm	dfy	ltr	$ntis$	$infl$	$eqis$	$svar$	dfr	tms	R^2
1	0.625	0.115	0.405	-0.199	-0.094	0.086	-3.459	-0.543	-0.141	0.810	-0.771	-0.621	0.736	1.059	-0.084	0.073
	(0.241)	(0.123)	(0.175)	(0.117)	(0.104)	(0.201)	(6.802)	(0.684)	(1.463)	(1.501)	(0.542)	(0.334)	(0.690)	(0.775)	(0.243)	
	[0.331]	[0.209]	[0.291]	[0.152]	[0.171]	[0.256]	[8.172]	[1.112]	[2.206]	[1.515]	[1.350]	[0.492]	[1.077]	[1.023]	[0.252]	
	{0.049}	{0.481}	{0.079}	{0.167}	{0.518}	{0.675}	{0.597}	{0.589}	{0.921}	{0.607}	{0.301}	{0.057}	{0.472}	{0.355}	{0.757}	
3	1.622	-0.055	1.198	-0.644	-0.080	-0.742	-15.572	-0.094	6.360	-1.197	0.356	-0.058	0.567	-0.604	0.448	0.384
	(0.442)	(0.214)	(0.322)	(0.178)	(0.197)	(0.460)	(11.655)	(1.425)	(2.154)	(1.399)	(1.669)	(0.413)	(1.470)	(1.603)	(0.218)	
	[0.902]	[0.317]	[0.392]	[0.227]	[0.324]	[0.533]	[20.651]	[3.015]	[4.874]	[4.006]	[2.199]	[1.033]	[3.077]	[2.399]	[0.601]	
	{0.000}	{0.848}	{0.000}	{0.004}	{0.702}	{0.027}	{0.116}	{0.994}	{0.035}	{0.566}	{0.746}	{0.930}	{0.757}	{0.638}	{0.313}	
5	3.004	0.070	1.888	-0.811	0.059	-1.233	-18.110	-1.064	10.943	-1.368	0.959	-0.449	1.467	-0.351	0.444	0.605
	(0.626)	(0.339)	(0.505)	(0.238)	(0.268)	(0.594)	(15.382)	(2.041)	(3.523)	(2.592)	(1.188)	(0.441)	(2.164)	(2.260)	(0.428)	
	[1.379]	[0.331]	[0.487]	[0.343]	[0.281]	[0.733]	[24.392]	[4.688]	[6.859]	[4.445]	[2.341]	[1.202]	[4.787]	[3.491]	[0.612]	
	{0.000}	{0.835}	{0.000}	{0.001}	{0.830}	{0.008}	{0.201}	{0.586}	{0.006}	{0.603}	{0.484}	{0.477}	{0.475}	{0.863}	{0.442}	
7	3.104	-0.096	1.400	-0.213	-0.100	-1.022	-19.406	3.155	13.372	-3.671	0.578	-0.196	-2.516	1.637	0.150	0.578
	(0.614)	(0.356)	(0.537)	(0.292)	(0.357)	(0.552)	(19.567)	(2.511)	(5.649)	(4.031)	(2.175)	(0.953)	(2.573)	(3.539)	(0.511)	
	[1.488]	[0.363]	[0.486]	[0.310]	[0.226]	[0.936]	[20.457]	[5.720]	[6.575]	[4.706]	[2.893]	[1.016]	[5.820]	[2.840]	[0.576]	
	{0.000}	{0.773}	{0.017}	{0.617}	{0.816}	{0.090}	{0.280}	{0.181}	{0.012}	{0.360}	{0.796}	{0.790}	{0.326}	{0.568}	{0.792}	
10	3.876	-0.080	1.865	0.383	-0.797	-2.069	-29.814	11.801	22.797	-14.515	8.795	0.458	-10.614	7.364	-0.052	0.737
	(0.811)	(0.404)	(0.540)	(0.265)	(0.391)	(1.131)	(28.247)	(2.644)	(6.250)	(3.759)	(3.343)	(0.963)	(2.578)	(2.594)	(0.587)	
	[1.501]	[0.427]	[0.658]	[0.356]	[0.226]	[1.192]	[21.430]	[6.342]	[7.143]	[5.819]	[2.904]	[0.939]	[6.518]	[2.705]	[0.630]	
	{0.000}	{0.891}	{0.027}	{0.421}	{0.090}	{0.007}	{0.184}	{0.000}	{0.004}	{0.006}	{0.000}	{0.652}	{0.001}	{0.082}	{0.993}	

Table 8: Out-of-sample (OOS) predictability

This table reports the results of one-year-ahead nested prediction comparisons for compounded market excess returns and real returns. The predictive variables are the log price-earnings ratio of $S\&P$ 500 index (pe), the volatility of market excess returns (V_{re}), the volatility of market real returns (V_{rr}), and the volatility of log price-earnings ratio (V_{pe}), respectively. The restricted (benchmark) model is the constant mean model in Panel A and the first-order autoregressive (AR(1)) model in Panel B. MSE_u is the mean-squared forecasting error from the relevant unrestricted model; MSE_r is the mean-squared error from the relevant restricted model. MSE-F represents the McCracken (2007) F-statistic; the null hypothesis is that the restricted and unrestricted models have equal mean-squared error (MSE); the alternative is that the restricted model has higher MSE. ENC-NEW gives the modified Harvey, Leybourne, and Newbold test statistic by Clark and McCracken (2001); the null hypothesis is that the restricted model encompasses the unrestricted model; the alternative is that the unrestricted model contains information that could be used to significantly improve the restricted model's forecast. The 95th percentile of the asymptotic distribution of the statistic as derived in Clark and McCracken (2001) is 1.518 for MSE-F and 2.085 for ENC-NEW. The OOS-R^2 is measured as the equation (12). The initial estimation period is thirty years, from 1937 to 1966. The model is recursively reestimated until 2023.

Panel A: Restricted model as constant mean model									
	Excess returns					Real returns			
	$\frac{MSE_u}{MSE_r}$	MSE-F	ENC-NEW	OOS-R^2		$\frac{MSE_u}{MSE_r}$	MSE-F	ENC-NEW	OOS-R^2
V_{pe}	0.973	2.331*	7.389*	0.027	V_{pe}	0.986	1.235	4.720*	0.014
pe	1.072	-5.619	3.091*	-0.072	pe	1.049	-3.886	2.840*	-0.049
V_{re}	1.048	-3.869	-1.703	-0.048	V_{rr}	1.072	-5.647	-2.254	-0.072
Panel B: Restricted model as AR(1) model									
	Excess returns					Real returns			
	$\frac{MSE_u}{MSE_r}$	MSE-F	ENC-NEW	OOS-R^2		$\frac{MSE_u}{MSE_r}$	MSE-F	ENC-NEW	OOS-R^2
V_{pe}	0.946	4.759*	11.757*	0.042	V_{pe}	0.962	3.348*	7.284*	0.027
pe	1.053	-4.232	3.893*	-0.066	pe	1.036	-2.922	3.461*	-0.048
V_{re}	1.048	-3.812	-1.786	-0.060	V_{rr}	1.083	-6.420	-2.792	-0.096

* indicates statistical significance at the 0.05 level.

Table 9: Predicting macroeconomic activities

This table reports univariate and multivariate long-horizon predictive regressions for compounded macroeconomic growths at horizons of $k = 1$, 3, 5, 7 and 10 years ahead. We consider three measures of macroeconomic growth, Gross Domestic Product growth (G_{GDP}), Personal Consumption Expenditures index growth (G_{PCE}) and Corporate Net Cash Flow growth (G_{NCF}). In Panel A, we conduct univariate analysis using the predictor V_{pe}. In Panel B, we conduct multivariate analysis with the predictors of V_{pe} and Fama-French three factors. The table reports estimates of OLS regression, Newey and West (1987) corrected standard errors (with k+1 lags) in parentheses, Hodrick (1992) standard errors (with k lags) in brackets, bootstrapping p-value in curly brackets and adjusted R-squared in the bottom line of each prediction horizon.

	Panel A: Univariate Analysis			Panel B: Multivariate Analysis		
k	$G_{GDP,t+k}$	$G_{PCE,t+k}$	$G_{NCF,t+k}$	$G_{GDP,t+k}$	$G_{PCE,t+k}$	$G_{NCF,t+k}$
1	-0.111	-0.139	-0.085	-0.135	-0.155	-0.045
	(0.049)	(0.045)	(0.176)	(0.054)	(0.049)	(0.171)
	[0.049]	[0.047]	[0.247]	[0.052]	[0.049]	[0.236]
	{0.034}	{0.001}	{0.655}	{0.009}	{0.001}	{0.787}
	0.046	0.121	-0.011	0.132	0.231	-0.044
3	-0.291	-0.368	-0.326	-0.322	-0.407	-0.408
	(0.141)	(0.142)	(0.350)	(0.166)	(0.168)	(0.328)
	[0.135]	[0.135]	[0.717]	[0.133]	[0.130]	[0.717]
	{0.010}	{0.001}	{0.189}	{0.008}	{0.001}	{0.119}
	0.080	0.151	0.012	0.084	0.162	0.054
5	-0.563	-0.637	-0.601	-0.709	-0.810	-1.038
	(0.261)	(0.263)	(0.567)	(0.337)	(0.347)	(0.645)
	[0.199]	[0.198]	[1.180]	[0.198]	[0.196]	[1.161]
	{0.001}	{0.001}	{0.042}	{0.001}	{0.001}	{0.013}
	0.138	0.177	0.044	0.157	0.197	0.076
7	-0.859	-0.949	-0.947	-1.315	-1.443	-2.058
	(0.402)	(0.405)	(0.662)	(0.603)	(0.613)	(0.925)
	[0.264]	[0.261]	[1.230]	[0.262]	[0.256]	[1.225]
	{0.001}	{0.001}	{0.004}	{0.001}	{0.001}	{0.001}
	0.170	0.200	0.100	0.190	0.221	0.193
10	-1.201	-1.331	-1.563	-2.447	-2.700	-3.860
	(0.620)	(0.623)	(0.851)	(1.151)	(1.164)	(1.598)
	[0.339]	[0.333]	[1.043]	[0.340]	[0.332]	[1.045]
	{0.003}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}
	0.160	0.187	0.196	0.188	0.218	0.276

Table 10: Predicting market volatility

This table reports estimates from regression of various market volatility measures on the volatility of log price-earnings ratio at horizons of $k = 1$, 3, 5, 7 and 10 years ahead. The dependent variables include volatility of market excess returns (V_{re}), volatility of market real returns (V_{rr}), and conditional volatility of market returns (V_m) based on the vector autoregressive model (VAR) following Bansal et al. (2014). The table reports estimates of OLS regression, Newey and West (1987) corrected standard errors (with k+1 lags) in parentheses, Hodrick (1992) standard errors (with k lags) in brackets, bootstrapping p-value in curly brackets and adjusted R-squared in the bottom line of each prediction horizon.

k	$V_{re,t+k}$	$V_{rr,t+k}$	$V_{m,t+k}$
1	0.196	0.217	-0.054
	(0.061)	(0.062)	(0.032)
	[0.058]	[0.058]	[0.026]
	{0.018}	{0.000}	{0.095}
	0.066	0.096	0.017
3	0.071	0.096	-0.074
	(0.079)	(0.081)	(0.036)
	[0.058]	[0.058]	[0.026]
	{0.309}	{0.113}	{0.013}
	0.002	0.016	0.055
5	-0.028	0.005	-0.042
	(0.076)	(0.080)	(0.032)
	[0.058]	[0.057]	[0.027]
	{0.620}	{0.965}	{0.163}
	-0.009	-0.012	0.009
7	-0.140	-0.105	-0.051
	(0.060)	(0.065)	(0.031)
	[0.059]	[0.058]	[0.029]
	{0.006}	{0.050}	{0.096}
	0.075	0.037	0.018
10	-0.227	-0.175	-0.083
	(0.062)	(0.065)	(0.053)
	[0.065]	[0.064]	[0.031]
	{0.001}	{0.001}	{0.021}
	0.226	0.135	0.062

Table 11: Volatility of log price-earnings ratio, cash flow shocks, discount rate shocks, and volatility shocks.

This table reports results from long-horizon predictive regressions for compounded market excess returns at horizons of $k = 1, 3, 5, 7$ and 10 years ahead. Panel A controls for future cash flow shocks using k-year ahead Gross Domestic Product growth (G_{GDP}), Personal Consumption Expenditures index growth (G_{PCE}) and Corporate Net Cash Flow growth (G_{NCF}). Panel B controls for the discount rate shocks using dividend yield(dp), term spread (tms) and default return spread(dfr). Panel C controls for the aggregate volatility shocks. V_{re}, V_{GDP}, V_{PCE} and V_{NCF} represent the volatility of market excess return, the volatility of Gross Domestic Product growth, Personal Consumption Expenditures index growth, and the volatility of Corporate Net Cash Flow growth, respectively. Panel D controls for all the cash flow shocks, discount rate shocks and volatility shocks. The table reports estimates of OLS regression, Newey and West (1987) corrected standard errors (with k+1 lags) in parentheses, Hodrick (1992) standard errors in brackets, bootstrapping p-value in curly brackets and adjusted R-squared (R^2) in the bottom line of each prediction horizon.

Panel A: Control for cash flow shocks					
k	1	3	5	7	10
			Univariate analysis		
V_{pe}	0.573	1.755	3.262	4.545	7.222
	(0.218)	(0.456)	(0.857)	(1.313)	(2.099)
	[0.306]	[0.830]	[1.317]	[1.671]	[1.953]
	{0.027}	{0.000}	{0.000}	{0.000}	{0.000}
R^2	0.047	0.180	0.256	0.258	0.289
			Multivariate analysis		
V_{pe}	0.657	1.408	2.528	3.191	4.954
	(0.278)	(0.578)	(0.856)	(1.193)	(1.562)
	[0.338]	[0.874]	[1.284]	[1.605]	[1.815]
	{0.023}	{0.004}	{0.000}	{0.000}	{0.004}
G_{GDP}	0.522	2.910	4.949	5.572	4.752
	(1.052)	(1.236)	(1.439)	(2.854)	(3.871)
	[1.250]	[1.656]	[1.618]	[2.057]	[2.219]
	{0.704}	{0.018}	{0.000}	{0.000}	{0.015}
G_{PCE}	0.194	-3.204	-4.981	-5.923	-5.233
	(1.232)	(1.144)	(1.163)	(2.501)	(3.186)
	[1.536]	[1.823]	[1.490]	[1.869]	[1.949]
	{0.879}	{0.015}	{0.001}	{0.001}	{0.004}
G_{NCF}	-0.018	0.057	-0.207	-0.043	0.061
	(0.211)	(0.226)	(0.278)	(0.362)	(0.567)
	[0.177]	[0.254]	[0.299]	[0.369]	[0.355]
	{0.918}	{0.753}	{0.348}	{0.923}	{0.851}
R^2	0.022	0.222	0.344	0.382	0.394

Panel B: Control for discount rate shocks					
k	1	3	5	7	10
			Univariate analysis		
V_{pe}	0.605	1.874	3.319	4.823	8.570
	(0.213)	(0.439)	(0.795)	(1.260)	(2.430)
	[0.298]	[0.812]	[1.281]	[1.630]	[2.000]
	{0.024}	{0.000}	{0.000}	{0.000}	{0.000}
R^2	0.053	0.184	0.259	0.294	0.333
			Multivariate analysis		
V_{pe}	0.522	1.692	2.875	3.919	6.711
	(0.188)	(0.344)	(0.503)	(0.657)	(1.211)
	[0.296]	[0.798]	[1.244]	[1.554]	[1.888]
	{0.019}	{0.000}	{0.000}	{0.000}	{0.000}
dp	0.088	0.217	0.441	0.670	1.057
	(0.035)	(0.070)	(0.096)	(0.150)	(0.268)
	[0.042]	[0.122]	[0.197]	[0.251]	[0.337]
	{0.031}	{0.003}	{0.000}	{0.000}	{0.000}
tms	1.289	3.739	9.870	11.832	17.064
	(1.052)	(1.974)	(2.638)	(3.813)	(4.503)
	[1.403]	[2.870]	[3.355]	[4.184]	[4.948]
	{0.336}	{0.097}	{0.000}	{0.004}	{0.003}
dfr	0.182	0.265	0.293	0.785	1.307
	(0.133)	(0.193)	(0.289)	(0.243)	(0.354)
	[0.152]	[0.187]	[0.207]	[0.260]	[0.310]
	{0.349}	{0.364}	{0.467}	{0.114}	{0.111}
R^2	0.094	0.277	0.473	0.544	0.560

Panel C: Control for aggregate volatility shocks					
k	1	3	5	7	10
Univariate analysis					
V_{pe}	0.573	1.755	3.262	4.545	7.222
	(0.218)	(0.456)	(0.857)	(1.313)	(2.099)
	[0.306]	[0.830]	[1.317]	[1.671]	[1.953]
	{0.044}	{0.000}	{0.000}	{0.000}	{0.000}
R^2	0.047	0.180	0.256	0.258	0.289
Multivariate analysis					
V_{pe}	0.572	1.621	3.621	4.057	6.452
	(0.233)	(0.581)	(0.946)	(0.959)	(1.383)
	[0.346]	[0.970]	[1.552]	[1.848]	[2.195]
	{0.078}	{0.000}	{0.000}	{0.000}	{0.000}
V_{re}	-0.710	-2.001	-4.135	-5.115	-5.782
	(0.475)	(1.327)	(2.025)	(2.151)	(3.926)
	[0.620]	[1.696]	[2.952]	[3.500]	[4.012]
	{0.295}	{0.059}	{0.013}	{0.015}	{0.062}
V_{GDP}	0.008	0.003	0.041	0.002	0.009
	(0.031)	(0.038)	(0.071)	(0.089)	(0.146)
	[0.031]	[0.055]	[0.064]	[0.069]	[0.097]
	{0.826}	{0.960}	{0.624}	{0.992}	{0.946}
V_{PCE}	-0.018	-0.033	-0.064	-0.069	-0.076
	(0.031)	(0.037)	(0.053)	(0.086)	(0.137)
	[0.031]	[0.049]	[0.068]	[0.075]	[0.095]
	{0.561}	{0.616}	{0.443}	{0.484}	{0.640}
V_{NCF}	0.002	0.009	0.007	0.058	0.066
	(0.002)	(0.003)	(0.010)	(0.016)	(0.022)
	[0.002]	[0.005]	[0.005]	[0.014]	[0.011]
	{0.499}	{0.041}	{0.299}	{0.000}	{0.000}
R^2	0.021	0.236	0.298	0.458	0.396

Panel D: Control for all					
k	1	3	5	7	10
			Univariate analysis		
V_{pe}	0.573	1.755	3.262	4.545	7.222
	(0.218)	(0.456)	(0.857)	(1.313)	(2.099)
	[0.306]	[0.830]	[1.317]	[1.671]	[1.953]
	{0.044}	{0.000}	{0.000}	{0.000}	{0.000}
R^2	0.047	0.180	0.256	0.258	0.289
			Multivariate analysis		
V_{pe}	0.685	1.278	2.555	2.178	1.787
	(0.271)	(0.434)	(0.601)	(0.637)	(1.404)
	[0.415]	[0.964]	[1.487]	[1.582]	[1.483]
	{0.040}	{0.005}	{0.000}	{0.004}	{0.179}
G_{GDP}	0.110	1.240	2.665	2.622	2.784
	(0.920)	(1.039)	(0.906)	(1.244)	(2.801)
	[1.293]	[1.708]	[1.538]	[1.661]	[1.844]
	{0.924}	{0.293}	{0.028}	{0.074}	{0.110}
G_{PCE}	1.541	-1.619	-3.117	-3.266	-3.477
	(1.401)	(0.942)	(0.878)	(1.111)	(2.197)
	[1.855]	[1.955]	[1.412]	[1.626]	[1.829]
	{0.339}	{0.208}	{0.009}	{0.006}	{0.032}
G_{NCF}	-0.107	-0.071	-0.138	-0.246	-0.350
	(0.191)	(0.182)	(0.157)	(0.198)	(0.490)
	[0.198]	[0.265]	[0.329]	[0.399]	[0.328]
	{0.543}	{0.745}	{0.526}	{0.286}	{0.305}
dp	0.107	0.318	0.630	0.887	1.304
	(0.041)	(0.063)	(0.089)	(0.074)	(0.179)
	[0.049]	[0.159]	[0.267]	[0.309]	[0.375]
	{0.035}	{0.000}	{0.000}	{0.000}	{0.000}
tms	1.069	3.531	9.323	7.037	7.944
	(1.019)	(1.589)	(2.218)	(3.465)	(2.751)
	[1.446]	[3.111]	[3.371]	[4.062]	[4.071]
	{0.482}	{0.097}	{0.000}	{0.029}	{0.098}
dfr	0.258	0.163	-0.067	0.549	0.718
	(0.178)	(0.268)	(0.312)	(0.320)	(0.604)
	[0.183]	[0.277]	[0.213]	[0.248]	[0.216]
	{0.197}	{0.616}	{0.844}	{0.188}	{0.301}
V_{re}	-1.189	-2.334	-4.176	-4.615	-4.628
	(0.485)	(1.119)	(1.685)	(1.080)	(4.450)
	[0.733]	[1.861]	[3.274]	[3.845]	[4.280]
	{0.053}	{0.026}	{0.003}	{0.011}	{0.118}
V_{GDP}	-0.001	-0.036	-0.021	-0.005	0.038
	(0.034)	(0.030)	(0.062)	(0.038)	(0.065)
	[0.033]	[0.058]	[0.056]	[0.047]	[0.059]
	{0.986}	{0.486}	{0.728}	{0.910}	{0.716}
V_{PCE}	-0.029	-0.001	-0.035	-0.059	-0.082
	(0.034)	(0.032)	(0.045)	(0.049)	(0.085)
	[0.035]	[0.060]	[0.072]	[0.062]	[0.076]
	{0.409}	{0.982}	{0.577}	{0.418}	{0.457}
V_{NCF}	0.003	0.010	0.006	0.028	0.029
	(0.002)	(0.004)	(0.003)	(0.010)	(0.015)
	[0.003]	[0.005]	[0.005]	[0.014]	[0.011]
	{0.237}	{0.017}	{0.240}	{0.005}	{0.074}
R^2	0.100	0.409	0.656	0.747	0.705

Appendix A The second-order dynamic price-earnings ratio model

Market gross return can be written as:

$$R_{t+1} = \frac{P_{t+1} + \Lambda_{t+1}E_{t+1}}{\Lambda_{t+1}E_{t+1}} \frac{\Lambda_{t+1}E_{t+1}}{\Lambda_t E_t} \frac{\Lambda_t E_t}{P_t} \tag{A.1}$$

where P, E, Λ and R are price, earning, dividend payout ratio and gross return of the market, respectively. Take logarithm to both sides of equation (A.1) yields

$$r_{t+1} = \Delta e_{t+1} + \lambda_{t+1} - pe_t + log(1 + e^{pe_{t+1}-\lambda_{t+1}}) \tag{A.2}$$

where $pe_t = p_t - e_t = logP_t - logE_t$, $\Delta e_{t+1} = e_{t+1} - e_t$, and $\lambda_t = log(\Lambda_t)$. For simplicity, we assume $\lambda_t = log(\bar{\Lambda}) + \gamma_t$.

Taking the second-order Taylor expansion, we obtain:

$$log(1 + e^{pe_{t+1}-\lambda_{t+1}}) = k + \rho(pe_{t+1} - \lambda_{t+1} - \bar{pe} + \bar{\lambda}) + \frac{1}{2}\rho(1-\rho)(pe_{t+1} - \lambda_{t+1} - \bar{pe} + \bar{\lambda})^2 \tag{A.3}$$

where $k = log(1 + e^{\bar{pe}-\bar{\lambda}}) = log(1 + e^{\bar{pd}})$ and $\rho = \frac{e^{\bar{pe}-\bar{\lambda}}}{1+e^{\bar{pe}-\bar{\lambda}}} = \frac{e^{\bar{pd}}}{1+e^{\bar{pd}}} > 0$. $\bar{pe}$ and $\bar{\lambda}$ are defined as the aggregate mean of log price-earnings ratio and log long-term target dividend payout ratio.

Then equation (A.2) can be written as,

$$\begin{aligned} r_{t+1} - \Delta e_{t+1} = k - \rho(\bar{pe} - \bar{\lambda}) - pe_t + \rho pe_{t+1} + (1-\rho)\lambda_{t+1} - \rho(1-\rho)(pe_{t+1} - \bar{pe})(\lambda_{t+1} - \bar{\lambda}) \\ + \frac{1}{2}\rho(1-\rho)(\lambda_{t+1} - \bar{\lambda})^2 + \frac{1}{2}\rho(1-\rho)(pe_{t+1} - \bar{pe})^2 \end{aligned} \tag{A.4}$$

Taking expectation based on the information set available at time t, we have

$$pe_t - \rho E_t pe_{t+1} = k - \rho\bar{pe} + \bar{\lambda} + \frac{1}{2}\rho(1-\rho)\kappa^2 + E_t(\Delta e_{t+1} - r_{t+1}) + \frac{1}{2}\rho(1-\rho)E_t(pe_{t+1} - \bar{pe})^2 \tag{A.5}$$

Note that $\lambda_{t+1} - \bar{\lambda} = \gamma_{t+1}$, a white noise.

Following Campbell and Shiller (1988) and Gao and Martin (2021), we derive a novel present value identify:

$$pe_t = \delta^* + E_t[\sum_{j=0}^{\infty} \rho^j (\Delta e_{t+1+j} - r_{t+1+j})] + \frac{1}{2}\rho(1-\rho)E_t[\sum_{j=0}^{\infty} \rho^j (pe_{t+1+j} - \bar{pe})^2] \tag{A.6}$$

where $\delta^* = \frac{1}{2}\rho\kappa^2 + \frac{k-\rho\bar{pe}+\bar{\lambda}}{1-\rho}$ contains all the constant items.

We also assume log price-earnings ratio follows AR(1) process. However, we relax the homoscedasticity assumption in Gao and Martin (2021) and allow time-varying conditional volatility of a state variable in the economy. It is important to note that this conditional volatility will directly affect the level and the volatility of log price-earnings ratio. Formally,

$$pe_{t+1} - \bar{pe} = \phi(pe_t - \bar{pe}) + \psi\sigma_t u_{t+1} \tag{A.7}$$

where $u_{t+1} \sim Ni.i.d(0,1)$ and σ_{t+1} denotes the conditional volatility reflecting time-varying economic uncertainty.

With the assumption of equation (A.7), we have

$$\begin{aligned}
&E_t[(pe_{t+1+j} - \bar{pe})^2] \\
&= E_t[(\phi(pe_{t+j} - \bar{pe}) + \psi\sigma_{t+j}u_{t+1+j})^2] \\
&= E_t[(\phi^{j+1}(pe_t - \bar{pe}) + \phi^j\psi\sigma_t u_{t+1} + \phi^{j-1}\psi\sigma_{t+1}u_{t+2} + ... + \psi\sigma_{t+j}u_{t+1+j})^2] \\
&= \phi^{2j}E_t[(pe_{t+1} - \bar{pe})^2] + E_t[\phi^{2(j-1)}\psi^2\sigma_{t+1}^2 u_{t+2}^2 + \phi^{2(j-2)}\psi^2\sigma_{t+2}^2 u_{t+3}^2 + ... + \psi^2\sigma_{t+j}^2 u_{t+1+j}^2]
\end{aligned} \tag{A.8}$$

Consider

$$E_t[\sigma_{t+j}^2 u_{t+1+j}^2] = E_t[E_{t+j}[\sigma_{t+j}^2 u_{t+1+j}^2]] = E_t[\sigma_{t+j}^2 E_{t+j}[u_{t+1+j}^2]] = E_t[\sigma_{t+j}^2] \tag{A.9}$$

Equation (A.8) becomes

$$
\begin{aligned}
&E_t[(pe_{t+1+j} - \bar{pe})^2] \\
&= \phi^{2j} E_t[(pe_{t+1} - \bar{pe})^2] + E_t[\phi^{2(j-1)}\psi^2\sigma_{t+1}^2 u_{t+2}^2 + \phi^{2(j-2)}\psi^2\sigma_{t+2}^2 u_{t+3}^2 + \dots + \psi^2\sigma_{t+j}^2 u_{t+1+j}^2] \\
&= \phi^{2j} E_t[(pe_{t+1} - \bar{pe})^2] + E_t[\phi^{2(j-1)}\psi^2\sigma_{t+1}^2 + \phi^{2(j-2)}\psi^2\sigma_{t+2}^2 + \dots + \psi^2\sigma_{t+j}^2] \\
&= \phi^{2j} E_t[(pe_{t+1} - \bar{pe})^2] + \psi^2 E_t \sum_{i=1}^{j} \phi^{2(j-i)}\sigma_{t+i}^2
\end{aligned}
\tag{A.10}
$$

and

$$
\begin{aligned}
&E_t[\sum_{j=0}^{\infty} \rho^j (pe_{t+1+j} - \bar{pe})^2] \\
&= E_t[\sum_{j=0}^{\infty} \rho^j \phi^{2j} [(pe_{t+1} - \bar{pe})^2] + \psi^2 E_t[\sum_{j=1}^{\infty} \rho^j \sum_{i=1}^{j} \phi^{2(j-i)}\sigma_{t+i}^2] \\
&= \frac{1}{1-\rho\phi^2} E_t[(pe_{t+1} - \bar{pe})^2] + \psi^2 E_t[\rho\sigma_{t+1}^2 + \rho^2(\phi^2\sigma_{t+1}^2 + \sigma_{t+2}^2) + \rho^3(\phi^4\sigma_{t+1}^2 + \phi^2\sigma_{t+2}^2 + \sigma_{t+3}^2) + \dots] \\
&= \frac{1}{1-\rho\phi^2} E_t[(pe_{t+1} - \bar{pe})^2] + \psi^2 E_t[\frac{\rho}{1-\rho\phi^2}\sigma_{t+1}^2 + \frac{\rho^2}{1-\rho\phi^2}\sigma_{t+2}^2 + \frac{\rho^3}{1-\rho\phi^2}\sigma_{t+3}^2 + \dots] \\
&= \frac{1}{1-\rho\phi^2} E_t[(pe_{t+1} - \bar{pe})^2] + \frac{\rho\psi^2}{1-\rho\phi^2} E_t[\sum_{j=0}^{\infty} \rho^j \sigma_{t+1+j}^2]
\end{aligned}
\tag{A.11}
$$

Substituting (A.11) into (A.6), we can derive

$$
pe_t - \pi E_t[(pe_{t+1} - \bar{pe})^2] = \delta^* + E_t[\sum_{j=0}^{\infty} \rho^j (\Delta e_{t+1+j} - r_{t+1+j}) + \nu\sigma_{t+1+j}^2] \tag{A.12}
$$

where $\pi = \frac{\rho(1-\rho)}{2(1-\rho\phi^2)}, \nu = \frac{\rho(1-\rho)\psi^2}{2(1-\rho\phi^2)}$.

Appendix B Additional Tables

Table B.1: Univariate predictive regressions for market returns

This table reports univariate long-horizon predictive regressions for compounded market excess returns (R_e) and real returns (R_r) at horizons of $k = 1$, 3, 5, 7 and 10 years ahead. The predictive variables are the volatility of log price-dividend ratio (V_{pd}), variance risk premium (vrp) in Bollerslev et al. (2009), and stock variance ($svar$) in Guo and Whitelaw (2006). The table reports estimates of OLS regression, Newey and West (1987) corrected standard errors (with k+1 lags) in parentheses, Hodrick (1992) standard errors (with k lags) in brackets, bootstrapping p-value in curly brackets and adjusted R-squared in the bottom line of each prediction horizon. The annual sample period is from 1937 to 2023.

	$R_{e,t+k}$			$R_{r,t+k}$		
k	V_{pd}	vrp	$svar$	V_{pd}	vrp	$svar$
1	0.063	0.311	0.559	-0.023	0.489	0.570
	(0.265)	(0.687)	(0.449)	(0.264)	(0.597)	(0.409)
	[0.258]	[0.920]	[0.703]	[0.260]	[0.830]	[0.673]
	{0.821}	{0.807}	{0.231}	{0.934}	{0.644}	{0.183}
	-0.011	-0.026	0.006	-0.012	-0.023	0.008
3	0.292	0.536	1.688	-0.115	0.748	1.389
	(0.673)	(1.413)	(1.163)	(0.662)	(1.352)	(1.186)
	[0.675]	[1.397]	[1.438]	[0.678]	[1.304]	[1.360]
	{0.530}	{0.766}	{0.020}	{0.781}	{0.682}	{0.047}
	-0.006	-0.028	0.037	-0.011	-0.026	0.025
5	0.979	1.292	2.162	-0.104	0.999	1.544
	(1.161)	(2.899)	(1.051)	(1.214)	(2.898)	(1.130)
	[1.025]	[1.390]	[2.175]	[1.011]	[1.427]	[2.111]
	{0.113}	{0.746}	{0.038}	{0.806}	{0.771}	{0.168}
	0.015	-0.027	0.028	-0.012	-0.029	0.010
7	1.727	0.664	1.981	-0.014	0.591	1.032
	(1.690)	(2.454)	(1.357)	(1.755)	(2.250)	(1.418)
	[1.281]	[1.157]	[2.265]	[1.302]	[1.148]	[2.242]
	{0.046}	{0.820}	{0.180}	{0.941}	{0.900}	{0.463}
	0.036	-0.033	0.010	-0.013	-0.034	-0.005
10	3.740	6.411	1.821	0.339	7.696	-0.893
	(2.713)	(2.519)	(2.555)	(2.632)	(3.438)	(2.305)
	[1.457]	[1.177]	[2.142]	[1.445]	[1.125]	[2.295]
	{0.006}	{0.250}	{0.408}	{0.871}	{0.173}	{0.657}
	0.076	0.012	-0.004	-0.012	0.028	-0.010

Table B.2: Multivariate forecast of quarterly stock returns

This table reports multivariate long-horizon predictive regressions for compounded market excess returns and real returns, at horizons of k = 1, 2, 3, 4, 12, 20, 28 and 40 quarters ahead. We consider three pairs of predictive variables, the log price-earnings ratio of $S\&P$ 500 index (pe) and the volatility of market excess returns (V_{re}) or the volatility of market real returns (V_{rr}), the log price-earnings ratio of $S\&P$ 500 index (pe) and the volatility of log price-earnings ratio (V_{pe}), and the volatility of market returns (V_{re} or V_{rr}) and the volatility of log price-earnings ratio (V_{pe}), respectively. The table reports estimates of OLS regression, Newey and West (1987) corrected standard errors (with k+1 lags) in parentheses, Hodrick (1992) standard errors (with k lags) in brackets, bootstrapping p-value in curly brackets and adjusted R-squared (R^2) of each prediction horizon. The sample period is from 1937: Q1 to 2023:Q4.

Panel A: Excess returns									
k	pe	V_{re}	R^2	pe	V_{pe}	R^2	V_{re}	V_{pe}	R^2
1	-0.012	-0.100	-0.001	-0.010	0.087	0.008	-0.078	0.088	0.007
	(0.015)	(0.161)		(0.014)	(0.039)		(0.154)	(0.039)	
	[0.013]	[0.275]		[0.015]	[0.051]		[0.282]	[0.050]	
	{0.318}	{0.409}		{0.340}	{0.041}		{0.534}	{0.044}	
2	-0.028	-0.181	0.004	-0.024	0.163	0.019	-0.125	0.163	0.014
	(0.028)	(0.265)		(0.026)	(0.070)		(0.251)	(0.070)	
	[0.026]	[0.548]		[0.031]	[0.100]		[0.566]	[0.098]	
	{0.091}	{0.291}		{0.114}	{0.013}		{0.421}	{0.009}	
3	-0.048	-0.250	0.012	-0.043	0.235	0.032	-0.151	0.235	0.020
	(0.038)	(0.346)		(0.035)	(0.101)		(0.328)	(0.103)	
	[0.038]	[0.843]		[0.047]	[0.148]		[0.869]	[0.145]	
	{0.017}	{0.242}		{0.035}	{0.004}		{0.430}	{0.003}	
4	-0.067	-0.295	0.021	-0.062	0.318	0.051	-0.154	0.315	0.029
	(0.045)	(0.406)		(0.042)	(0.131)		(0.387)	(0.134)	
	[0.050]	[1.155]		[0.062]	[0.194]		[1.188]	[0.190]	
	{0.005}	{0.212}		{0.003}	{0.000}		{0.588}	{0.004}	
12	-0.189	0.018	0.066	-0.199	1.215	0.235	0.387	1.181	0.158
	(0.113)	(1.146)		(0.100)	(0.271)		(1.088)	(0.312)	
	[0.119]	[3.606]		[0.155]	[0.491]		[3.661]	[0.498]	
	{0.001}	{0.953}		{0.001}	{0.000}		{0.305}	{0.000}	
20	-0.252	1.439	0.083	-0.310	2.148	0.302	1.873	2.061	0.247
	(0.234)	(1.517)		(0.195)	(0.502)		(1.228)	(0.575)	
	[0.170]	[5.656]		[0.201]	[0.670]		[5.637]	[0.693]	
	{0.001}	{0.009}		{0.001}	{0.000}		{0.000}	{0.000}	
28	-0.450	2.670	0.155	-0.512	3.258	0.392	3.357	3.188	0.319
	(0.362)	(1.635)		(0.281)	(0.765)		(0.968)	(0.930)	
	[0.219]	[2.167]		[0.219]	[0.683]		[2.155]	[0.675]	
	{0.001}	{0.000}		{0.001}	{0.000}		{0.000}	{0.000}	
40	-0.779	6.581	0.247	-0.824	6.029	0.455	7.365	6.091	0.432
	(0.560)	(3.018)		(0.419)	(1.160)		(1.890)	(1.629)	
	[0.289]	[2.909]		[0.292]	[1.027]		[2.889]	[0.989]	
	{0.001}	{0.000}		{0.001}	{0.000}		{0.000}	{0.000}	

Panel B: Real returns									
k	pe	V_{re}	R^2	pe	V_{pe}	R^2	V_{re}	V_{pe}	R^2
1	-0.011	-0.154	0.001	-0.007	0.070	0.003	-0.134	0.073	0.006
	(0.015)	(0.167)		(0.014)	(0.039)		(0.159)	(0.040)	
	[0.013]	[0.280]		[0.015]	[0.051]		[0.286]	[0.050]	
	{0.309}	{0.175}		{0.521}	{0.083}		{0.225}	{0.079}	
2	-0.027	-0.293	0.007	-0.020	0.129	0.010	-0.237	0.133	0.011
	(0.028)	(0.273)		(0.026)	(0.071)		(0.258)	(0.072)	
	[0.026]	[0.555]		[0.032]	[0.101]		[0.571]	[0.098]	
	{0.123}	{0.100}		{0.234}	{0.053}		{0.145}	{0.045}	
3	-0.047	-0.427	0.016	-0.037	0.186	0.019	-0.323	0.190	0.016
	(0.038)	(0.350)		(0.034)	(0.103)		(0.328)	(0.105)	
	[0.038]	[0.854]		[0.048]	[0.148]		[0.878]	[0.145]	
	{0.012}	{0.042}		{0.067}	{0.024}		{0.110}	{0.020}	
4	-0.068	-0.547	0.027	-0.056	0.253	0.033	-0.393	0.257	0.023
	(0.045)	(0.399)		(0.041)	(0.134)		(0.372)	(0.138)	
	[0.050]	[1.168]		[0.063]	[0.195]		[1.200]	[0.190]	
	{0.001}	{0.024}		{0.009}	{0.011}		{0.085}	{0.011}	
12	-0.212	-1.058	0.079	-0.194	1.030	0.175	-0.607	1.013	0.110
	(0.101)	(0.893)		(0.084)	(0.299)		(0.863)	(0.349)	
	[0.120]	[3.625]		[0.156]	[0.492]		[3.677]	[0.500]	
	{0.001}	{0.006}		{0.001}	{0.000}		{0.142}	{0.000}	
20	-0.315	-1.292	0.077	-0.304	1.795	0.225	-0.677	1.746	0.149
	(0.206)	(1.136)		(0.169)	(0.576)		(0.886)	(0.696)	
	[0.172]	[5.767]		[0.202]	[0.674]		[5.731]	[0.703]	
	{0.001}	{0.048}		{0.001}	{0.000}		{0.219}	{0.000}	
28	-0.574	-1.878	0.146	-0.528	2.828	0.333	-0.852	2.851	0.200
	(0.317)	(1.597)		(0.253)	(0.937)		(1.014)	(1.211)	
	[0.222]	[2.225]		[0.221]	[0.686]		[2.202]	[0.676]	
	{0.001}	{0.017}		{0.001}	{0.000}		{0.240}	{0.000}	
40	-1.054	-1.975	0.238	-0.912	5.312	0.497	-0.506	5.727	0.305
	(0.468)	(2.907)		(0.293)	(1.485)		(1.849)	(2.122)	
	[0.294]	[3.025]		[0.296]	[1.028]		[2.993]	[0.991]	
	{0.001}	{0.060}		{0.001}	{0.000}		{0.578}	{0.000}	

Table B.3: Predicting macroeconomic activities

This table reports estimates from regression of compounded macroeconomic growths on the volatility of price-earnings ratio (V_{pe}) while controlling market risk premium ($R_m - R_f$), HML and SMB from Fama-French Research Factors. The dependent variables are the compounded Gross Domestic Product (GDP) growth (G_{GDP}), Personal Consumption Expenditures index (PCE) growth and Corporate Net Cash Flow (NCF) growth. The table reports OLS estimates of regressors, Newey and West (1987) corrected standard errors (with k+1 lags) in parentheses, Hodrick (1992) standard errors (with k lags) in brackets, bootstrapping p-value in curly brackets and adjusted R-squared (R^2) of each prediction horizon.

	Panel A: GDP Growth					Panel B: PCE Growth					Panel C: NCF Growth				
k	V_{pe}	$R_m - R_f$	HML	SMB	R^2	V_{pe}	$R_m - R_f$	HML	SMB	R^2					
1	-0.135	0.039	0.014	0.070	0.132	-0.155	0.022	0.009	0.076	0.231	-0.045	-0.073	-0.030	-0.004	-0.044
	(0.054)	(0.022)	(0.023)	(0.036)		(0.049)	(0.020)	(0.023)	(0.033)		(0.171)	(0.060)	(0.112)	(0.092)	
	[0.052]	[0.024]	[0.030]	[0.033]		[0.049]	[0.022]	[0.030]	[0.032]		[0.236]	[0.076]	[0.095]	[0.090]	
	{0.009}	{0.073}	{0.600}	{0.040}		{0.001}	{0.230}	{0.665}	{0.008}		{0.787}	{0.429}	{0.779}	{0.978}	
3	-0.322	-0.018	0.053	0.122	0.084	-0.407	-0.031	0.028	0.136	0.162	-0.408	-0.216	-0.073	-0.034	0.054
	(0.166)	(0.045)	(0.059)	(0.105)		(0.168)	(0.051)	(0.058)	(0.107)		(0.328)	(0.086)	(0.116)	(0.197)	
	[0.133]	[0.028]	[0.044]	[0.065]		[0.130]	[0.027]	[0.046]	[0.063]		[0.717]	[0.102]	[0.098]	[0.188]	
	{0.008}	{0.724}	{0.371}	{0.128}		{0.001}	{0.582}	{0.663}	{0.055}		{0.119}	{0.096}	{0.616}	{0.844}	
5	-0.709	-0.073	0.111	0.215	0.157	-0.810	-0.076	0.094	0.241	0.197	-1.038	-0.152	0.017	-0.087	0.076
	(0.337)	(0.068)	(0.102)	(0.161)		(0.347)	(0.083)	(0.100)	(0.181)		(0.645)	(0.131)	(0.206)	(0.233)	
	[0.198]	[0.038]	[0.040]	[0.075]		[0.196]	[0.033]	[0.036]	[0.074]		[1.161]	[0.127]	[0.158]	[0.269]	
	{0.001}	{0.469}	{0.344}	{0.103}		{0.001}	{0.429}	{0.413}	{0.067}		{0.013}	{0.361}	{0.892}	{0.731}	
7	-1.315	-0.113	0.091	0.328	0.190	-1.443	-0.119	0.118	0.357	0.221	-2.058	-0.162	-0.019	-0.081	0.193
	(0.603)	(0.142)	(0.130)	(0.245)		(0.613)	(0.156)	(0.139)	(0.274)		(0.925)	(0.192)	(0.250)	(0.298)	
	[0.262]	[0.046]	[0.039]	[0.092]		[0.256]	[0.042]	[0.038]	[0.079]		[1.225]	[0.134]	[0.145]	[0.249]	
	{0.001}	{0.429}	{0.645}	{0.096}		{0.001}	{0.410}	{0.484}	{0.059}		{0.001}	{0.462}	{0.927}	{0.785}	
10	-2.447	-0.099	0.068	0.519	0.188	-2.700	-0.125	0.082	0.594	0.218	-3.860	-0.231	0.209	0.347	0.276
	(1.151)	(0.236)	(0.185)	(0.362)		(1.164)	(0.265)	(0.202)	(0.406)		(1.598)	(0.276)	(0.366)	(0.304)	
	[0.340]	[0.056]	[0.034]	[0.089]		[0.332]	[0.050]	[0.033]	[0.080]		[1.045]	[0.149]	[0.133]	[0.271]	
	{0.001}	{0.656}	{0.855}	{0.107}		{0.001}	{0.585}	{0.826}	{0.095}		{0.001}	{0.438}	{0.645}	{0.439}	