Q-Group submission for Jack Treynor Prize: Research Statement
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In our study, we provide evidence in favor of the economic and statistical strength of aggregate stock return predictability. In particular, a novel recursively estimated survey-based measure of investors' return extrapolation bias is used as a state-variable in traditional predictive regressions that link price-scaled variables to future stock market returns. In conditional forecasting regressions of excess returns on horizons up to a year, we find that price-scaled variables predict future stock returns only when the degree of extrapolation (DOX) measure is high i.e. when investors' assessment of future stock returns is based on fewer recent observations. This is because as investors rely on a shorter set of returns to form current expectations, such expectations experience on average quicker correction, as fewer subsequent new returns in the future are sufficient to erase any temporary biased optimism/pessimism about the stock market. At the same one-year horizon, stock return predictability by price-scaled variables instead appears absent in states of low DOX, due to the stickiness of expectations in such states.

These findings, which are consistent with the return predictability insights of the model of Barberis, Greenwood, Jin, and Shleifer (2015), are relevant to practitioners for two main reasons. First, knowledge of our DOX measure allows investors to decide whether to use a high D/P ratio as a signal of future higher stock market returns. Our results suggest that when DOX is high (one standard deviation higher than its median value), a 1% higher D/P ratio is followed by a statistically significant 26% increase in the expected equity premium the following year. When instead the DOX is low (one standard deviation lower than its median value), the same increase in the dividend-price ratio is *negatively*, but insignificantly, related to future returns, and predicts a 2% lower equity premium in the upcoming year. Therefore, asset managers would want to increase their positions in stocks when the D/P is high i.e. prices are depressed, and DOX is high, but they might decide to reduce their exposure to stocks in a low DOX state. Arguably more important is the ability of our model to predict negative stock market returns. Approximately 15% of our monthly forecasts of year-ahead excess returns are negative and directionally accurate. A negative equity premium prediction arises when market overvaluation (i.e. a low D/P) is accompanied by a high DOX (i.e. a high likelihood of correction in expectations). Negative aggregate market realizations may correspond to bad times, when investors' marginal utility of consumption is higher. Having a forecasting model that allows one to reallocate funds outside of the stock market prior to a crash is therefore extremely valuable since it allows investors to craft strategies that offer good performance at a critical time. To provide a further quantification of the benefit of using our conditional predictive model for capital allocation decision, we estimate that an agent endowed with \$100 in June of 1997 would have collected \$410 by December of 2013, a 20% higher terminal wealth than the one achieved with a passive buy-and-hold strategy. This represents an improvement of up to 100% over an agent who only uses the D/P ratio to forecast returns.

The second reason is more subtle but nonetheless paramount. Traditionally, return predictability has been explained with time series variation in the risk-return tradeoff. In the risk-return story, an asset manager who uses a high dividend-price ratio to forecast a bullish stock market in the near future may earn higher returns which are purely a reflection of larger discount rates: the asset manager takes more risk, and hence earns higher return. Our novel result calls into question this interpretation as the only plausible one, and instead proposes that a low D/P ratio i.e. high prices relative to fundamentals, may be due widespread irrational extrapolative expectations. Under this alternative view, the higher profits of a market timing strategy such as ours are not mere compensation for higher risk, and correspond instead to truly abnormal returns.

Extrapolation bias and the predictability of stock returns by price-scaled variables*

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Abstract

Using survey data on expectations of future stock returns, we recursively estimate the degree of extrapolation bias (DOX) in investor expectations. There is considerable time-series variation in the DOX, and it interacts significantly with price-scaled variables in predictive regressions. In particular, we show that the ability of the dividend-price ratio to predict the equity premium is contingent on the DOX. There is strong predictability when the DOX is high, while the predictability disappears when the degree of extrapolation bias is low. Additionally, following the intuition from the present-value identity, we find that the lack of return predictability in low-DOX states comes with higher persistence of the D/P ratio. These results extend to the use of the book-to-market and earnings-to-price ratios, and are corroborated by out-of-sample evidence. Our findings have important implications. They support the interpretation of price-scaled variables as proxies for asset mispricing, and they help answer a critical question: when will an overvalued asset, or even a bubble, experience a correction?

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1 Introduction

Ample evidence suggests that aggregate stock returns are predictable. The work of Fama and French (1988), Campbell and Shiller (1988), Cochrane (1991, 2007, 2011), and Lewellen (2004), among others, documents that the dividend-price (D/P), the book-to-market (B/M), and the earnings-to-price (E/P) ratios can predict future returns. Time-series predictability of stock market returns by price-scaled variables is often attributed to time-series variation in investors' required returns, suggesting a risk-based explanation.[1] Yet, behavioral theorists propose that predictability may arise because prices temporarily deviate from the level warranted by fundamentals due to the existence of irrational traders who hold biased beliefs.[2] Motivated by the arguments in these behavioral models, we investigate the extent to which time series variation in biased beliefs can account for the observed predictability relation between price-scaled variables and future stock returns.

Determining the role behavioral biases play in the extant evidence of return predictability is no easy task because a researcher must assess both the existence and the extent of bias in investors' expectations. Recent work by Greenwood and Shleifer (2014) fills this gap by providing evidence of one such bias in investors' beliefs: *overextrapolation*.[3] The authors show that surveys of investors' expectations of future stock market returns are a direct and reliable measure of beliefs, and that survey data provides evidence of a significant degree of extrapolation bias in investor expectations. In a related work, Barberis, Greenwood, Jin, and Shleifer (2015) present an equilibrium model of financial markets with heterogeneous investors and biased beliefs in which an increasing degree of extrapolation bias leads to stronger stock return predictability by the dividend-price ratio.[4]

In our study, we use survey data on stock market expectations to quantify the extrapolation bias in investors' beliefs and document considerable variation in aggregate extrapolation bias over time. We then test the implications of such variation for the predictability of the equity premium by price-scaled variables. In conditional forecasting regressions of excess returns on horizons up to a year, we find that price-scaled variables predict future stock returns only when the degree of overextrapolation is high, while these variables hold no predictive ability when the degree of overextrapolation is low. This result is confirmed by out-of-sample tests and applies to stock

[1]Literature has shown that time-series variation in required compensation for risk may arise due to variation in i) risk aversion (Campbell and Cochrane 1999), ii) aggregate consumption risk (Bansal and Yaron 2004; Bansal, Kiku, and Yaron 2012), iii) rare-disaster risk (Gabaix 2008), iv) risk-sharing opportunities among heterogeneous agents (Lustig and Van Nieuwerburgh 2005), and v) beliefs (Timmermann 1993; Detemple and Murthy 1994).

[2]Mispricing as an equilibrium outcome may arise if rational investors find it optimal not to offset irrational investors' trades (De Long, Shleifer, Summers, and Waldmann 1990; Shleifer and Vishny 1997; Barberis, Greenwood, Jin, and Shleifer 2015), or if they may profit from *riding a bubble* (Abreu and Brunnermeier 2003).

[3]Throughout the paper, we use the terms extrapolative expectations, overextrapolation, and extrapolation bias interchangeably. An extrapolative investor believes that recent high returns are more likely to be followed by high returns, and similarly, recent low returns are more likely to be followed by low returns. This is consistent with the law of small numbers of Kahneman and Tversky (1971) and with the hot-hands fallacy of Gilovich, Tversky, and Vallone (1985) in which "people expect the essential characteristics of a chance process to be represented not only globally in the entire sequence, but also locally." As a consequence, they draw general conclusions about the underlying data generating process by relying too heavily on relatively small sequences of data.

[4]Other studies that examine the role of extrapolation in financial markets are Lansing (2006), Hirshleifer and Yu (2011), and Choi and Mertens (2015).

return predictability by the dividend-price, book-to-market, and earnings-to-price ratios.

This study makes several contributions. First, it provides evidence in favor of the economic and statistical strength of return predictability. In particular, instead of offering a new predictor, we show that if we reexamine the common predictors of future returns through the behavioral lens of extrapolation bias, the dynamics of aggregate stock returns are better understood. Second, the results support the insight of the model of Barberis, Greenwood, Jin, and Shleifer (2015; hereafter BGJS), who established a theoretical link between the predictive power of the D/P ratio and the degree of extrapolation bias in investors' beliefs. Third, the evidence presented in this paper calls into question the prior interpretation of price-scaled variables, such as the D/P or B/M ratios as proxies for time-varying risk premia, as well as the consensus knowledge that time variation in risk-reward tradeoff is solely responsible for stock return predictability. Fourth, we show that time-series variation in investors' degree of extrapolation bias reconciles recent evidence of instability in the predictive relation between price-scaled variables and future returns. Fifth, by documenting that a survey-based state variable allows us to better understand the relationship between aggregate quantities set in equilibrium, such as returns and price-ratios, we reinforce the message in Greenwood and Shleifer (2014): survey expectations contain useful information on widely held economic beliefs.

To estimate the degree of extrapolation bias, we use a nonlinear least squares regression in which survey expectations of future stock market returns are regressed on quarterly stock returns lagged up to 60 quarters. The degree of extrapolation bias (DOX) is measured as the relative loading of expectations on the returns in the most recent quarter compared to returns in more distant ones. If future index returns are only weakly correlated with recent returns, an excessive reliance of expectations on recent stock market performance (a high DOX) suggests that investors overextrapolate recent returns too much into the future. Our full sample estimates of DOX and serial correlation in index returns confirm this is indeed the case. Our DOX estimates extracted from survey data point to a significant degree of overextrapolation in investor expectations. For example, in the period 1992:06–2014:12, our full sample DOX estimate obtained using the Investor Intelligence Survey implies that the loading of survey expectations on the returns over the most recent quarter is 16 times higher than the loading only four quarters earlier.[5] During the same period, serial correlation in consecutive quarterly stock market returns is only 7%, and serial correlation between consecutive yearly returns is actually a negative 5%, thus lending support to the interpretation that investors on average *over*extrapolate recent market returns into the future.

The mechanism that links the degree of overextrapolation to stock return predictability by price-scaled variables is straightforward. If the degree of extrapolation bias is high, investors easily overreact to recent stock performance, since a short streak of good (bad) news makes them too bullish (bearish) about future returns. Irrationally high (low) expectations induce an irrational

[5] This means that, when forming expectations, investors view returns four quarters earlier as only 6% as important as those in the most recent quarter. Using a similar specification, Greenwood and Shleifer (2014) find that across a large number of independent surveys of investors' expectations, the average weight attributed to current quarterly returns is approximately 10 times the average weight assigned to returns four quarters earlier.

demand for stocks, which pushes prices too high (low) relative to fundamentals. As a result, the D/P ratio declines (increases). This conjecture is in line with the negative correlation between survey expectations and price-scaled variables observed in the data. On average, this overvaluation (undervaluation) is not sustained in the future, as extrapolators observe new returns which do not support their initial optimism (pessimism). As extrapolators' expectations are corrected, the initial shock to the D/P ratio reverts to the mean in the future, and a low (high) dividend-price ratio today is on average followed by low (high) prices in the future. This is consistent with the positive association between D/P ratio and future stock returns that is documented empirically. As suggested by the present-value model of Campbell and Shiller (1988), as well as the arguments in Cochrane (2005, 2007), mean-reversion in the D/P ratio is a central feature of stock return predictability. In the framework of BGJS, when extrapolators exhibit a higher degree of extrapolation bias (i.e. a higher DOX), they form expectations by relying heavily on recent stock return realizations. Consequently, few new return observations can quickly lead to significant changes in expectations. For this reason, a high degree of extrapolation bias implies stronger mean reversion in the dividend-price ratio, and hence stronger stock return predictability. Therefore, we claim that the predictive power of the D/P ratio is related to the degree of extrapolation bias: a higher DOX (along with a large deviation of the D/P ratio from its long-run mean) signals misvaluation. This leads to eventual price correction, mean-reversion in the D/P ratio, and stronger stock return predictability. Similar arguments can be made for other widely used price-scaled predictors of the equity premium.

To test the implications of the proposed mechanism empirically, one needs time series variation in the degree of the extrapolation bias. We argue that there are reasons to believe, ex-ante, that the DOX is time-varying. First, stock market participation rates by different groups of investors (e.g. young versus old) may be time-varying and result in changes of "consensus" extrapolation through time. Second, investors' perception of the relative informativeness of recent stock market returns may change over time, as a function of the features exhibited by new return realizations. To capture this time series variation, we recursively estimate DOX using survey expectations of future returns.[6] This provides a measure, in real time, of extrapolators' tendency to overweigh more recent return realizations when forming their beliefs. After estimating the DOX time-series, we conduct formal tests to understand why the degree of extrapolation bias changes over time. Consistent with our hypothesis above, we show that the DOX is significantly linked to the relative participation rates of young versus old investors in the stock market.

In our main tests, we run conditional stock return predictability regressions in which the DOX acts as a state variable and is interacted with the dividend-price ratio. We show that stock return predictability by price-ratios is conditional on the DOX. For example, in the period 1992:06–2013:12, we find that when the degree of overextrapolation is 0.71 (one standard deviation higher than its median value), a one standard deviation rise in D/P ratio is followed by a statistically significant 26% increase in the expected equity premium the following year. When instead the DOX is 0.31

[6] By using only lagged returns in our recursive estimation, we avoid look-ahead bias in our predictability tests.

(one standard deviation lower than its median value), the same increase in the dividend-price ratio is *negatively*, but insignificantly, related to future returns, and predicts a 2% lower equity premium in the upcoming year.[7] Interestingly, approximately 15% of our monthly forecasts of year-ahead excess returns are negative and directionally accurate. A negative equity premium prediction arises when market overvaluation (i.e. a low D/P) is accompanied with a high DOX (i.e. a high likelihood of correction in expectations). This evidence that our model can accurately predict a negative risk premium can hardly be reconciled with rational models of risk. We obtain similar results for other price-scaled predictors, such as B/M and the E/P ratio.[8]

This main finding, documenting the significant conditional role of DOX in predictive regressions involving price-scaled variables, has important implications. Our findings suggest that simply observing overvaluation in the marketplace as measured by high P/D ratios does not necessarily mean that the market will soon experience a correction. The market may instead become even more overvalued. It is critical to understand when such mispricing will correct. Our study helps answer this age-old question, namely, when will an overvalued asset correct back to fair value? We show that when an asset is overvalued and investor beliefs load on distant past returns (low DOX), the overvaluation is unlikely to correct soon. This is because when investors put considerable weight on distant past returns when forming expectations, they are unlikely to shift their expectations quickly and cause a correction. On the other hand, when an asset is overvalued and investor beliefs load heavily on recent returns (high DOX), there is a high chance of correction. In this case, even one period of bad news can quickly result in a significant change in expectations. Similar arguments can be made when an asset is undervalued. Given that we are using aggregate price-scaled variables to predict the equity premium, these arguments can be generalized to aggregate stock market correction. To the extent that aggregate stock market overvaluation is the main source of an impending stock market crash, as in the dot-com bubble, our methodology helps us understand when a market overvaluation or even a bubble will experience a correction.

In our second test, we find that when the DOX is low, price-scaled variables are more persistent and hence predict themselves. This is consistent with Cochrane's (2007) conjecture that if the dividend-price ratio does not predict returns, it must predict either dividend-growth or a future D/P ratio. In particular, at a year horizon when the DOX is one standard deviation below (above) its median value, the D/P ratio has an autoregressive coefficient of approximately 0.88 (0.43). In other words, in periods of relatively low DOX, the half-life of a shock to the D/P ratio is approximately five years, while it is only 10 months when the DOX is relatively high.

In our third test, we assess the extent to which the extrapolation bias can explain the evidence in prior literature that the relationship between price-scaled predictors and future returns varies over

[7]Unless otherwise stated, all the results discussed in the introduction refer to the use of the DOX extracted from the principal component of the Investor Intelligence and the American Association of Individual Investors surveys.

[8]It is important to note that the conditioning role of the DOX does not simply reflect return continuation or reversal, nor does it simply capture changes in investor sentiment or business cycle variation. When we augment our conditional predictive regressions with the Baker and Wurgler (2006) market-based measure of sentiment, or with business cycle variables such as growth in industrial production or recession indicators, our results are confirmed and those variables our subsumed by the DOX.

time (Viceira 1996; Paye and Timmermann 2006; Lettau and Van Nieuwerburgh 2008; Henkel, Martin, and Nardari 2011). We argue that variation in the extent of time series predictability of stock returns may arise because investors' expectations are on average more extrapolative in some periods, and less extrapolative in others. When the average DOX in the sample window is large, expectations are less persistent and corrected more quickly, with a consequent increase in the estimated predictability coefficient in those periods. Lower average DOX corresponds to more persistent expectations and an accompanying decline in predictability. By recursively estimating both the univariate predictive regressions of one-year ahead excess returns on current dividend-price ratio, and the average DOX over a 20-year moving window, we not only confirm prior evidence of parameter instability, but we also find that better predictability is indeed obtained in periods characterized by higher average DOX. Furthermore, variation in average DOX across sample periods can explain 70% of the documented instability in the univariate predictability relation.[9]

In order to provide additional support for our in-sample findings, we conduct out-of-sample tests in the spirit of Goyal and Welch (2008). First, we perform statistical tests of improvement in forecasting accuracy when migrating from the traditional univariate predictive regression to the conditional model (Clark and West 2007; Rapach, Strauss, and Zhou 2010). Then we assess the ex-post average utility gains reaped by an expected utility maximizer with mean-variance preferences when she uses the conditional instead of the traditional model (Campbell and Thompson (2008)). Our results speak to the superiority of the conditional specification and support our in-sample results. More specifically, the univariate model, as well as the naive forecasting methodology, always exhibit a statistically higher mean-squared-forecast-error (MSFE) compared to the conditional model. The univariate model, however, is rarely an improvement over a simple forecast based on the historical average return on the market. Furthermore, considerable economic benefits arise from using our new model. At a yearly rebalancing frequency, we document that portfolio mean returns improve by 30% to 50% when moving from a univariate model to its conditional counterpart. We also find larger Sharpe ratios for the conditional model across price-scaled variables and horizons. For example, when using the D/P ratio as a predictor of future one-year ahead excess returns, the Sharpe ratio obtained using the conditional model is 0.43, versus 0.16 of the univariate model, and 0.12 of the historical average model. The difference is greater when the D/P is replaced with the B/M and E/P ratios, and the finding is common across surveys.

This study shares its general topic of inquiry with Bacchetta, Mertens, and Wincoop (2009), Amromin and Sharpe (2013), and Koijen, Schmeling, and Vrugt (2015). These studies all provide evidence of an irrational component in investors' expectations. Our study is motivated by the work of Greenwood and Shleifer (2014) and BGJS. We differ by capturing the time-series variation in extrapolation bias and interacting our DOX measure with the price-scaled variables to shed light on the time-varying return predictability by these variables. In our study, DOX reflects the transitory nature of extrapolators' expectations, and it also indicates if the level of price-scaled

[9] As we show later in the robustness section, a proxy for countercyclical risk premia such as the NBER recession indicator can only match 2% of the witnessed variation in stock return predictability.

variables signals misvaluation due to extrapolative beliefs. Neither the D/P ratio nor the DOX necessarily carries predictive ability by itself; however stock return predictability becomes stronger when a high level of mispricing is coupled with highly transitory irrational beliefs (i.e. a high or low D/P ratio is observed in a high-DOX state).

Our study also joins other literature which argues that behavioral biases can lead to time-series predictability of stock returns. For example, Nelson (1995) and Baker and Wurgler (2000) show that the equity share of new issues is a powerful predictor of future returns. This is consistent with the hypothesis that corporations may reduce their cost of capital by issuing equity in periods of high sentiment and equity overpricing. Yu and Yuan (2012) document that the nearness to the Dow 52-week high predicts future stock returns, which is consistent with limited investor attention and anchoring bias. Baker, Wurgler, and Yuan (2012) show that the investor sentiment measure of Baker and Wurgler (2006) predicts future stock returns. Like these studies, our work presents evidence of a behavioral explanation for return predictability. Yet, we refrain from proposing new predictors. We instead focus on price-scaled variables, and show that (i) their ability to predict future returns, traditionally linked to time-varying discount rates, is conditional on the degree of extrapolation bias in investors' expectations, and (ii) the significance of DOX in interacting with price-scaled variables is not affected by controlling for the investor sentiment measure or business cycle variables.

The remainder of the paper is organized as follows. Section 2 develops the main empirical hypothesis. Section 3 presents the econometric framework. Section 4 briefly describes the data, while Section 5 discusses the in-sample and out-of-sample results. Section 6 includes robustness tests, and Section 7 concludes with final remarks and ideas for future research.

2 Hypothesis Development

2.1 Present-value model

To motivate our study, we rely on the present-value model of Campbell and Shiller (1988):

$$r_{t,t+1} = \Delta d_{t,t+1} + [dp_t - \rho dp_{t+1}] \tag{1}$$

where r is log raw return, dp is log dividend-price ratio, Δd is the log dividend-growth, and ρ is a constant whose historical value is 0.96. All quantities are demeaned. Equation 1 states that the future return on a risky security is higher because the security will pay higher dividends in the future, or because the equilibrium price per unit of dividend will increase. Focusing on the conditioning information I=$\{dp, \Delta d, r\}$ one can posit that:

$$\Delta d_{t,t+1} = \epsilon^{\Delta d}_{t+1} \tag{2}$$

and

$$dp_{t+1} = \Psi dp_t + \epsilon_{t+1}^{dp} \tag{3}$$

Equation 2 states that consistent with evidence in Cochrane (2005, 2007), the best estimate of the future level of dividends is the current dividend level. Equation 3 models the dp as an AR(1) process with persistence coefficient Ψ. Substituting Equations 2 and 3 into Equation 1, we obtain:

$$r_{t,t+1} = dp_t(1 - \rho\Psi) + \epsilon_{t+1}^{\Delta d} - \rho\epsilon_{t+1}^{dp} \tag{4}$$

Equation 4 suggests that if one runs a univariate linear predictive regression of future returns on current dp, the predictability coefficient is $(1 - \rho\Psi)$. This coefficient is a function of the mean-reverting behavior exhibited by the dp ratio. If the dividend-price ratio is persistent, i.e. Ψ is high, an increase (decline) in prices today is less indicative of lower (higher) prices tomorrow. Consequently, a univariate predictive regression shows little marginal predictive power of the dividend-price ratio, and the best forecast of the future return is the unconditional mean. When instead the dividend-price ratio mean-reverts more quickly, i.e. Ψ is low, a shock to prices will quickly mean revert, and the predictability coefficient is large.

On one hand, Equation 4 suggests that the extent to which a price-scaled variable such as the D/P ratio can predict future returns depends on how quickly the dividend-price ratio mean reverts. On the other hand, the simple equation above is silent on the economic forces behind such mean-reversion. Below we argue that the presence of the extrapolation bias in investors' expectations may result in the aforementioned mean-reversion, and hence may explain stock return predictability.

2.2 Extrapolation and return predictability

The investigation of a potential link between extrapolation of past returns by market participants and aggregate stock return predictability rests on a few assumptions. The first is that individuals have extrapolative expectations. DeBondt (1993), Clarke and Statman (1998), Amromin and Sharpe (2014), and Greenwood and Shleifer (2014) find evidence of extrapolation bias in survey-based forecasts of future returns. Similarly, Tversky and Kahneman (1974) and Andreassen and Kraus (1990) offer evidence of extrapolation bias in experimental settings.

The second assumption is that individuals act in accordance with their extrapolative beliefs. Given that most evidence of overextrapolation is based either on surveys or on experimental results, and in both environments there may be lack of sufficient incentive to elicit true expectations, a discrepancy between individuals' beliefs and their subsequent actions is possible. Gennaioli, Yueran, and Shleifer (2015) use individual-level responses to the Graham and Harvey survey of CFOs' expectations to provide evidence of consistency of CFOs' extrapolative forecast of future firm growth, and their subsequent planned and realized investments. Similarly, Greenwood and Shleifer (2014) show that aggregate survey expectations of future market returns, which display an extrapolative nature, correlate positively with aggregate mutual fund inflows. This again suggests that survey responses and subsequent actions are aligned.

The last assumption is that rational investors fail to instantly correct the mispricing caused by extrapolative investors, and therefore extrapolation matters in equilibrium. Individual-level biased beliefs may affect individual-level decisions and still not matter in equilibrium, since a rational investor may act immediately to correct the mispricing caused by an extrapolator. This argument critically relies on rational investors' willingness and ability to correct such mispricing. In this respect, a vast theoretical literature that includes De Long, Shleifer, Summers, and Waldmann (1990), Cutler, Poterba, and Summers (1990), Shleifer and Vishny (1997), and Abreu and Brunnermeier (2003) among others, calls into question the notion that it is always in a rational investor's best interest to bet against her irrational counterpart.

Building on this evidence of the pervasiveness of extrapolation in the economy, and on its likely effect on equilibrium prices, the theoretical model of BGJS (2015) is the first to provide an extrapolation-based explanation for the extant evidence of predictability. In the model, if the extrapolative investors in the economy form expectations of future returns by relying more heavily on recent stock returns (i.e. the DOX is high), the dividend-price ratio mean-reverts more quickly (lower Ψ). Therefore we take expectations on both sides of Equation 4 and rewrite it as follows:[10]

$$E_t[r_{t,t+1}] \simeq (DOX)dp_t \tag{5}$$

While BGJS (2015) provide a novel comparative statics result, an empirical test of the implications of their model requires variation (either in the time-series or in the cross-section) in the degree of overextrapolation. Below we provide arguments for the ex-ante assertion that the degree of extrapolation bias is time-varying. We then measure the extent of such variation, and test its implications for stock return predictability.

2.3 Time-varying degree of extrapolation bias

The aggregate degree of overextrapolation may change over time as per the experience-based learning evidence of Malmendier and Nagel (2011). Young individuals, who base their forecast of future returns on a shorter macroeconomic history, intrinsically extrapolate using a higher DOX. Older investors, who have instead witnessed a longer return time-series, implicitly adopt a lower DOX. Over time, stock market participation rates by the two groups change as a reflection of their own experience of the stock market (Nagel, 2012). This causes an alteration to the mix of active investors, which may cause the *consensus* DOX to change over time.

There is also a second potential channel that causes time-series variation in DOX. Griffin and Tversky (1992) document that when making predictions based on new information, individuals are sensitive to its perceived strength (expressed in terms of salience and extremeness) and may overreact relative to a rational forecaster. Salience and extremeness are context-dependent and hardly quantifiable. Here we focus on features of the returns themselves that might make them more salient

[10] Equation 5 is only an approximation, because ρ is set to one (rather than its historical value of 0.96,) and we assume a specific relationship between Ψ and the DOX. Instead, a monotonic decreasing relation between Ψ and DOX suffices to link a rise in DOX to a rise in stock return predictability by the D/P ratio.

to investors. For example, the extremeness of a return realization might be positively correlated with its perceived strength. This is consistent with Yuan (2015), who finds that attention-grabbing events may deeply affect investor trading patterns. Similarly, the informativeness attributed by an investor to a return realization may depend on the pattern that generated that return, as in Da, Gurun, and Warachka (2014). Later, in Section 5.1 we document times-series variation in the DOX empirically. In Section 5.2 we show that, consistent with the intuitions above, time-series variation in DOX is indeed associated with time-series variation in the relative participation of young versus old investors to the stock market. The salience-based explanations of variation in DOX explain only a small percentage of the documented variation in the degree of overextrapolation.

3 Econometric approach

Motivated by the above arguments and following Greenwood and Shleifer (2014), we model extrapolative expectations as follows:

$$\begin{aligned} Exp_t &= a + b\sum_{i=0}^{\infty} w_i R_{t-(i+1)\Delta t, t-i\Delta t} \\ w_i &= \frac{\lambda^i}{\sum\limits_{k=0}^{\infty} \lambda^k}\ ,\ \ 0 \leq \lambda < 1 \end{aligned} \tag{6}$$

where Exp_t refers to extrapolators' expectations as of time t (obtained from survey data), and $R_{i,j}$ is the return realized between time i and time j. Equation 6 states that expectations are a function of past return realizations in which the weights placed on historical returns feature a geometric decay. Δt determines the frequency of return observations. Following prior literature, we choose $\Delta t = 1/4$ and use quarterly returns. A lower λ implies that investors place higher weight on more recent observations, while earlier observations contribute less to an extrapolator's expectations. For example, when $\lambda = 0.85$, investors place twice as much weight on the most recent return realization compared to returns only four quarters earlier. The relative weight is 10 times higher compared to the weight four quarters earlier when $\lambda = 0.55$. The smoothness coefficient, λ, plays a significant role in this framework, since a lower λ is associated with both possible overreaction and with lower persistence in the beliefs of extrapolators. Figure 1 shows simulation results that illustrate these aspects of λ. In the figure, that fixes the coefficient b to 1, we assume that at time $t = -1$ extrapolators' expectations of annual returns are at their long-run mean value of approximately 10%. At time $t = 0$, a quarterly return of 5% is realized and incorporated into expectations. We then report the average value of subsequent extrapolators' expectations obtained by simulating 5000 time-series of subsequent returns.[11] Figure 1 presents results for four different

[11] Simulated quarterly returns are generated by matching mean and variance of the historical quarterly returns of the CRSP value-weighted portfolio in the period 1990–2014. Serial correlation in quarterly returns could potentially change the shape of investors' expectations reported in Figure 1. Nevertheless, as reported above, the historical

values of λ, and shows that while extrapolators always revise their expectations following a new return realization, the extent of their reaction as well as the speed of subsequent mean reversion in beliefs are larger when λ is low.

To assess how time series variation in extrapolation bias interacts with price-scaled variables in predicting stock returns, we first estimate Equation 6 by nonlinear least squares and extract the DOX, measured as $1 - \lambda$. Time series variation in DOX is captured by estimating the equation recursively over time.[12] One key parameter in the recursive estimation is the length of the estimation window. Instead of arbitrarily choosing a fixed window length, we follow Pesaran and Timmermann (2007) and Capistran and Timmermann (2009) and endogenize window selection by combining estimates obtained using different window sizes.[13] Specifically, every month, m, we estimate Equation 6 using three alternative window sizes of 24, 36, 48 months, and an expanding window whose starting length is 36 months.[14] We use month *m-12* to *m-1* as a cross-validation period, in which we assess the one-step ahead MSFE of our model for each alternative window size. We then calculate a weighted average of the DOX estimates obtained from each window size for month m, where the weights assigned are proportional to the inverse of the MSFE obtained in the cross-validation period.

Once we estimate the DOX time-series, we use it as a conditioning variable in traditional predictive regressions of l-months ahead cumulative excess return $R_{t,t+l}$ on the lagged dividend-price ratio (and other price-scaled variables such as B/M and the E/P ratios). Specifically, we estimate the following linear model:

$$R_{t,t+l} = (a_0 + a_1 DOX_t) + D/P_t(b_0 + b_1 DOX_t) + \epsilon^R_{t,t+l} \tag{7}$$

The null hypothesis of no or negative effect of extrapolation on stock return predictability by the D/P ratio and the alternative one-sided hypothesis of an increase in predictability as the DOX increases, are:

$$H_0 : b_1 \leq 0 \qquad H_a : b_1 > 0 \tag{8}$$

Later, we explore two other implications of the alternative hypothesis. The first concerns the autoregressive behavior of price-scaled predictors of the equity premium, and posits that such predictors should revert to the mean more quickly when DOX is high. The second explores the link between parameter instability in the predictability relation and time-series variation in the DOX, and argues that periods of stronger predictability are those in which average DOX is higher.

autocorrelation of quarterly returns is low, and we choose to not consider it in our simulations.

[12] Recursive estimations only use historical data to avoid look-ahead bias in the measurement of the DOX estimation and in predictive regressions.

[13] Later, for robustness, we repeat our tests with a fixed window of 36 months, and show that results are similar.

[14] The inclusion of the expanding window serves the purpose of explicitly allowing for a constant DOX. If the DOX doesn't change over time, it is efficient to use all available observations, and the MSFE-based method should consistently place higher weight on the expanding window estimate than on the competing rolling-window estimates. Empirically, we find that this is rarely the case.

4 Data

In our study, we rely on surveys of expectations of future stock market returns in the US. For statistical power and comparability with prior studies, we focus solely on the two longest available surveys.[15] The Investor Intelligence Survey (II) collects forecasts of stock market performance since 1963 from newsletters of financial advisors in the United States. AA is the survey of retail investors from the American Association of Individual Investors, which started in 1987. In Table 1, we report general information about survey data as well as summary statistics.

Both II and AA collect qualitative data and report the difference between the percentage of polled investors who are bullish and the percentage of polled investors who are bearish about future stock market performance. While qualitative and quantitative expectations may be different, like Greenwood and Shleifer (2014) we argue that qualitative survey data is a good proxy for quantitative expectations. To support this claim, we include in Table 1 data on a UBS/Gallup survey (*Gallup ER*) that was conducted for a short period of time between 1998 and 2004, and elicited quantitative forecasts. As the pairwise correlation statistics in panel C show, Gallup ER is highly correlated with both II (46%) and AA (53%). For this reason, we consider qualitative expectations data as a close substitute for quantitative data. Table 1 also presents summary statistics for the principal component of II and AA, (PC), which spans the period 1987:06–2014:12. Later, in our main tests, we focus on the period 1987:07–2014:12, in which both surveys and their principal component are available.

Panel B of Table 1 provides summary statistics on price-scaled variables and excess returns. The dividend-price (D/P) ratio is a 12-month moving sum of dividends paid on the S&P 500 index, normalized by the most recent price. Fama and French (1988) find that a high D/P ratio is associated with higher returns on horizons that range from one to five years. Campbell and Shiller (1988) complement this finding by showing that the positive association between D/P and subsequent total return can be justified in the context of the simple present-value relation in Equation 1. The book-to-market (B/M) ratio, whose predictive ability has been studied by Pontiff and Schall (1998), Kothari and Shanken (1999), and Lewellen (1999), is the ratio of book value to market value for the Dow Jones Industrial Average. Finally, the cyclically adjusted earnings-to-price (E/P) ratio, considered as a predictor of aggregate stock returns by Campbell and Shiller (1988, 2001), is a 10-year moving average of earnings on the S&P 500 index, normalized by the current price.[16] The equity premium is defined as the difference between the return on the CRSP value-weighted portfolio, and the risk-free rate of return.[17] Panel B of Table 1 confirms the evidence in prior literature that price-scaled variables are persistent. Additionally, the monthly nature of our data causes yearly excess returns to be serially correlated at a quarter lag, while the correlation

[15] Golez (2014) and Da, Jagannathan, and Shen (2015) are two recent papers whose sample period is almost identical to ours.

[16] D/P and B/M are from Amit Goyal's website (http://www.hec.unil.ch/agoyal), while E/P is from Robert Shiller's website (http://www.econ.yale.edu/ shiller/data.htm).

[17] The latter is from Ken French's website (http://www.mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

between non-overlapping returns is close to zero.

Panel C of Table 1 shows high correlation among surveys, which suggests that independently collected data on investors' expectations tell a consistent story. Furthermore, the PC is approximately 90% correlated with both II and AA. This high correlation justifies its use as a representative series. The panel also shows that expectations of future returns are negatively correlated with price-scaled variables, which is consistent with the notion that improving expectations are associated with a growth in prices relative to fundamentals. Lastly, the extrapolative nature of survey-based expectations is reflected in the high correlation between survey forecasts of future returns, and the returns accumulated over the course of the year.

5 Results

5.1 Degree of overextrapolation

For each survey, we first estimate Equation 6 in the full sample using nonlinear least squares. The infinite summation in Equation 6 is not amenable to estimation. Following Greenwood and Shleifer (2014) and BGJS, we choose a number of lags equal to 60. The estimated λ coefficient is then mapped onto the corresponding DOX $= 1 - \lambda$, which is reported in Table 2.

The full sample DOX extracted from II is 0.5, which corresponds to a weight on the most recent quarterly return that is 16 times larger than the weight assigned to the return four quarters earlier. In the case of the DOX measured from AA, there is even greater evidence of overextrapolation, since recent quarterly returns are given 55 times more weight compared to quarterly returns realized a year earlier. As expected, the principal component series exhibits a full-sample DOX of 0.6 that lies between the II and AA estimates.

Next, we use a dynamic-window combination methodology to capture time-series variation in the DOX. In Table 3, we present summary statistics for the individual surveys as well as for their principal component PC. The recursive methodology generates DOX estimates for the period 1992:06–2014:12, since five years are needed to initialize the window-selection algorithm. There is considerable variation in DOX over time. Figure 2 plots the estimated DOX time-series for the principal component of II and AA. The graph shows that the DOX estimates span the entire range of the coefficient, which can only lie between 0 and 1. Additionally, the DOX time-series appears to move in lockstep with salient events in the recent history of the stock market. For instance, the DOX progressively increases in the decade leading up to the dot-com bubble burst, reaches a peak during the first half of 2000, and later declines back to its pre-bubble levels by the end of 2004. The investors' degree of extrapolation bias reaches a peak again in 2007, right before the great recession, and it declines again by mid-2010. Table 3 also presents summary statistics for an additional DOX time-series, which we henceforth refer to as PC_{ext}. It is constructed using the DOX extracted from II during the period 1967:12–1992:05, and the DOX extracted from the principal component time-series for the subsequent period 1992:06–2014:12. Later, in Section 5.5, we use this extended DOX time-series to show that time-variation in the DOX can explain a large portion of the witnessed variation in the predictive relationship between stock returns and price-scaled variables.

5.2 Potential determinants of the DOX

In this section, we follow up on our discussion above on the possible determinants of time-series variation in DOX. We test two possible explanations of such variation, namely changes in the population of active stock market investors, and changes in salience of observed stock market returns. A time-varying composition of the pool of stock market investors may cause the consensus DOX to change over time, if different types of investors rely on recent versus older stock market return realizations differently. Recent literature suggests that age and lifetime experiences may play a key role in expectations formation (Nagel 2012, Malmendier and Nagel 2015), and in portfolio allocation decisions (Malmendier and Nagel 2011). An application of the findings in that literature to the return extrapolation framework in Equation 6 suggests that young individuals, who have experienced a shorter return history, place more weight on recent returns, relative to the weight assigned to such returns by older individuals. A higher reliance on recent returns makes the expectations of the Young more prone to shocks, and more likely to undergo a reversal in the future. On the other hand, old investors present more persistent expectations. As new returns are realized, young and old investors adjust their expectations of future returns, and make the decision whether or not to enter the stock market. When the participation rate of younger individuals increases, and their presence in the market relative to the older investors grows, the average DOX increases as well. Salience may also play a role in time-series variation in DOX, to the extent that different features of any given return realization may prompt higher or lower adjustment to investor expectations, and induce quicker or slower reversal in expectations.

We measure time-series variation in the participation of different age-groups to the equity market by using triennial data from the Survey of Consumer Finances (SCF).[18] We construct a ratio of the number of young (50 years of age or below) to old (above 50 years of age) investors with direct holdings of stocks by complementing SCF data with demographic data from the U.S. Census.[19] When measuring return salience, we concentrate on return volatility (DeBondt (1993)) and return extremeness (Yu and Yuan (2012)).[20] We work with detrended data as in Nagel (2012).

The results of our analysis are reported in Table 4. In univariate regressions, we find support for the hypothesis that the variation in DOX is related to the variation in the stock market participation rate of young versus old investors. In regression (1), we document that when the number of young investors in the stock market increases relative to the number of older investors, the DOX increases. Figure 3 illustrates this high degree of comovement between DOX and the relative stock market participation measure. We then decompose this overall effect by regressing DOX on the

[18] http://www.federalreserve.gov/econresdata/scf/scfindex.htm The data are converted to monthly frequency by spline interpolation.

[19] https://www.census.gov/hhes/families/data/households.html.

[20] Volatility is estimated from daily data, as in French, Schwert, and Stambaugh (1986). Return extremeness is measured by means of a dummy variable which is equal to one when a quarterly return is more than 2 standard deviations away from its unconditional mean, and zero otherwise.

participation rates of the Young and the Old. In regression (2), we show that when controlling for the participation rate of the Young, an increase in the participation of the Old corresponds to a decline in DOX. On the contrary, holding the participation rate of the Old constant, an increase in the participation of the Young is associated to higher DOX. We then turn to the role of return salience. We find, in regression (3), that an increase in intra-quarter volatility is associated to an increase in DOX, consistent with the intuitive notion that volatility may caution investors against using older return data to forecast the market when it appears to be volatile. We also find that the realization of an extreme quarterly return usually prompts investors to react comparatively less, and hold on to the expectations held before. Finally, when we horse-race the market participation variables with the salience proxies, in regressions (4) and (5), we provide additional ground for a participation-based explanation of time-series variation in DOX, while the marginal effect of our proxies for salience weakens in statistical terms. In conclusion, it appears that the variation in DOX that we capture recursively using survey data may be a consequence of changes in the participation of different groups of investors in the stock market across time.

5.3 Conditional stock return predictability

Once the time-series variation in the degree of overextrapolation is unveiled, we can run a formal test of the hypothesis that the extrapolation bias may be a determinant of stock return predictability by price-scaled variables. To this end, we estimate the conditional model in Equation 7. We focus on excess return predictability, and Table 5 presents the main results.[21] Our sample period is 1992:06–2013:12. Panel A refers to the use of the D/P ratio, while in Panels B and C, we replace it with the B/M and the E/P ratio, respectively. We report results for prediction horizons of three and 12 months. Since we use monthly observations, one concern is serial correlation in the error-terms due to the overlapping nature of our return observations. We address this issue by adopting Newey-West (1987) standard errors with three and 12 lags. Finally, Table 5 reports the result of a baseline univariate predictability regression for each sample period. This replicates prior findings of stock return predictability, and hence is the natural benchmark for our new model.

Panels A through C of Table 5 present four significant findings. First, the coefficient estimate on the interaction term, b_1, is always positive and statistically significant, which is consistent with our hypothesis that stock return predictability by price-scaled variables increases with investors' degree of extrapolation bias, and with the model of BGJS. Second, when moving from the standard univariate regression to the conditioning predictability model, there is a considerable improvement in goodness of fit, as captured by the adjusted-R^2. For example, at the year horizon, a predictive regression that features the dividend-price ratio alone has an adjusted-R^2 of 16%, while the conditional specification that uses the DOX data from the II series brings the goodness of fit to 23%. The improvement is even stronger when the AA or the PC DOX is used as a conditioning

[21]Later, we show that our results extend to raw returns, capital gains, and the use predictability of log excess returns.

variable. In these cases, the adjusted-R^2 increases to 50%. The improvement in the model's ability to match variation in future aggregate stock returns does not simply come from the addition of DOX as an explanatory variable. As the last column of each panel shows, a bivariate regression of future returns on current price-scaled predictor and current DOX delivers slight improvements to the adjusted-R^2 over the baseline univariate case, and in some cases the marginal impact of the DOX is not statistically significant. Similar conclusions can be drawn for different horizons. Third, when return predictability is assessed in the traditional univariate regression framework, the resulting predictability coefficient always lies somewhere between the minimum (b_0) and maximum ($b_0 + b_1$) values of the conditional predictability coefficient($b_t = b_0 + b_1 DOX_t$). Intuitively, given a theory that posits different degrees of stock return predictability across DOX states, a univariate regression measures an average relationship that includes episodes of high and low DOX. In so doing, the use of the univariate predictive regression framework may understate or overstate the extent of predictability at any given time. Fourth, in 15% of our monthly predictions of year-ahead aggregate excess returns, our conditional model predicts, correctly, a subsequent negative equity premium. The negative equity premium prediction arises in cases of high DOX and low D/P ratio (i.e. in an overvalued market with highly transitory beliefs). In these instances, we test the null hypothesis that the model prediction is positive or zero, and we reject it at the 1% level in 70% of the cases.[22] The finding of a statistically significant negative equity premium prediction matched by subsequent realized negative excess returns is strong evidence that stock return predictability by D/P ratio in high DOX states can hardly be reconciled with rational models of risk in which the ex-ante equity premium is positive. Similar results are obtained using other price-scaled predictors.

In Panel D of Table 5, we follow Aiken and West (1991), and present the conditional coefficient of predictability $b_t = [b_0 + b_1 DOX_t]$, and its related t-statistic for a set of representative values of the DOX state-variable. In what follows, we refer to high DOX as a value of the degree-of-overextrapolation coefficient that is one standard deviation above the DOX sample median, and we refer to a low DOX as a value of the degree-of-extrapolation bias that is one standard deviation below the DOX sample median. For brevity, Panel D only focuses on the DOX extracted from the principal-component series, and similar results are obtained when the DOX from II or AA is used.

The results are striking, and confirm that the predictive ability of price-scaled variables is contingent on investors' degree of overextrapolation. When the degree of overextrapolation is high, a one standard deviation (0.01) increase in the D/P ratio is followed by a statistically significant 26% increase in the expected equity premium the following year. When instead the DOX is low, a one-standard deviation increase in the D/P is *negatively*, but insignificantly related to future returns, and predicts a 2% lower equity premium in the upcoming year. Similar results are obtained using other price-ratios. For instance, when we replace the D/P ratio with the B/M ratio, a one-standard deviation (0.27) rise in B/M predicts a 47% higher excess return the next year when the DOX is high, while the same rise corresponds to a 16% decline in future returns if the DOX is low.[23] In

[22] See Baker and Wurgler (2000) for a similar test.

[23] In the model of BGJS, even when DOX is low, D/P should still have predictive power for returns in the long-term. In unreported tests, we find that this is indeed the case. The predictive power of D/P for low-DOX states increases

conclusion, Table 5 shows that the the D/P ratio, as well as other price-scaled predictors, forecasts future returns differently across DOX-states, and in a statistically significant way only when the DOX is high.

To complement our discussion of the results in Table 5, Figure 4 presents evidence of conditional one-year predictability. In the figure, we provide scatter plots of the relationship between D/P, B/M, or E/P and future 12-month excess returns, conditioned on values of the DOX parameter that are either below (left panel) or above (right panel) the median DOX. We focus on the *PC* DOX time-series. The figure shows a large wedge between stock return predictability in states of high and low degree of extrapolation bias. For instance, there is a strong and positive association between current D/P ratio and future aggregate returns in high DOX states, in which variation in dividend-price accounts for 35% (Panel A) of variation in the subsequent equity premium. On the other hand, there is little or no predictability in states of low DOX, where the R^2 is only 0.7%. Similar results can be inferred for the other price-ratios considered. Therefore, the figure supports the findings in Table 5.

While the results presented here are consistent with a behavioral interpretation of the evidence of stock return predictability, one needs to interpret them with caution. The combination of a short sample period, persistent regressors, high contemporaneous correlation between price-scaled predictors and future returns, as well as overlapping observations, may justify concerns of small sample bias and size distortions in our inference. In Section 6 we address these issues via bootstrapping techniques and show that, while the aforementioned concerns are valid, correcting for small sample bias alters neither the sign nor the magnitude of our coefficient of interest on the interaction of DOX and a given price-scaled predictor. In particular, we find that under the null of no conditioning role of DOX for stock return predictability, the bootstrapped interaction coefficient is on average only 5% as large as the in-sample estimated coefficient. Furthermore, our in-sample estimated interaction coefficient places on average at the 94^{th} percentile of its bootstrapped distribution obtained under the null of no conditional predictability. The highest degree of rejection of the null is obtained when DOX is interacted with B/M or E/P. This is evidence that while bias and size distortions exist in coefficient estimation, our basic results in Table 5 carry over after correcting for these issues.

In conclusion, our results suggest that the time-series predictability of stock returns by price-scaled variable is a phenomenon contingent on the degree of extrapolation bias and on the time-varying tendency of extrapolators to predominantly rely on too few recent return realizations. Furthermore, the traditional univariate approach to time-series predictability of stock returns only measures an average relationship between the coefficients, and the strength of this relation improves when we condition on a high degree of overextrapolation.

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with the horizon. The D/P coefficient eventually becomes positive for a return horizon beyond 30 months.

5.4 Mean reversion in price-scaled predictors

In Section 3 we argue, based on the Campbell and Shiller (1988) decomposition, that the predictability of aggregate excess stock returns by the dividend-price ratio should decline as D/P becomes more persistent. The results of our conditional predictability regressions suggest that the predictive ability of the D/P ratio is apparent only in states of high DOX. Therefore the D/P ratio should exhibit different persistence across DOX-states. It is expected to be more (less) persistent in low (high) DOX states.[24]

$$D/P_{t+l} = (a_0 + a_1 DOX_t) + D/P_t(b_0 + b_1 DOX_t) + \epsilon^{dp}_{t,t+l} \tag{9}$$

In particular, the null and alternative hypotheses are:

$$H_0 : b_1 \geq 0 \quad H_a : b_1 < 0 \tag{10}$$

Under the null hypothesis, the coefficient b_1 on the interaction term in Equation 9 is positive or zero. The alternative hypothesis postulates that as the DOX increases, the dividend-price ratio reverts to the mean more quickly, and is hence a negative sign of the coefficient b_1.

Panel A of Table 6 presents the results at a yearly forecast horizon for the sample period 1992:06–2013:12. In Panel B we provide further evidence by reporting the half life of a shock to a price-scaled variable in states of high versus low DOX. As in prior tables, we refer to high DOX as the degree of overextrapolation that is one standard-deviation above its sample median, and similarly we define a low DOX as one-standard deviation below its sample mean.

The table results warrant a rejection of the null hypothesis, since in all cases the coefficient on the interaction term is negative, and in all but one case, the coefficient is statistically significant at the 5% level. Panel B reveals that shocks to price-scaled variables under a low DOX are persistent, and their half-life has a median value of five years. When in states of high DOX, shocks to price-scaled variables appear to be reabsorbed much more quickly, since their half-life decreases to approximately 10 months.[25]

Based on the results in Tables 5 and 6, and consistent with the intuition from the Campbell and Shiller (1988) model, we can establish a parallel between the autoregressive behavior of price-scaled predictors and their ability to forecast future returns: an increase in investors' degree of overextrapolation bias is associated with both better predictability and quicker mean reversion in predictor variables. Conversely, if the DOX is low, price-scaled predictors exhibit a high autocorrelation, which reduces their ability to predict future equity premium.

[24] The D/P ratio does not have to be persistent in low DOX states. The mean-reversion of the dividend-price ratio might still occur in low-DOX states, provided that there is dividend-growth predictability in such states.

[25] In unreported results, we also bootstrap the regression in Equation 9 to correct for the Kendall (1954) small sample attenuation bias of the autoregressive coefficient b_0. As expected, correcting for the bias increases the AR(1) coefficient estimate further, while it has little to no effect on the interaction coefficient b_1, thus lending even further support to our findings.

5.5 Parameter instability in the predictability relation

Prior studies of stock return predictability have claimed that the association between price-scaled predictors and future returns is time-varying. In Figure 5, we provide evidence of such instability by presenting the recursively estimated univariate predictability coefficient of the dividend-price ratio on future one-year excess returns. In the period 1987:12–2013:12, we obtain the recursively estimated coefficient of predictability β_{RW_m} by fitting every month, m, the following predictive regression of year-ahead excess returns over a rolling window of 20 years:

$$R_{t,t+12} = a_0 + \beta_{RW_m} D/P_t + \epsilon^R_{t,t+12}$$

where $t \in [m - 20 \times 12 + 1, m]$, R stands for aggregate excess return on the value-weighted portfolio of CRSP US equities, and D/P is the dividend-price ratio. Figure 5 also reports a 20-year moving average DOX ($\overline{DOX_{RW_m}}$) extracted from the extended principal component PC_{ext}. Under the null of no conditioning role of investors' degree of overextrapolation for the time-series predictability of the equity premium, there should be no apparent relationship between β_{RW_m} and $\overline{DOX_{RW_m}}$. In other words, a period of higher average DOX should not be characterized by better predictability compared to a period of low average DOX. Under the alternative hypothesis, the predictive ability of a price-scaled variable should be positively correlated with the in-sample prevailing DOX. Indeed, the content of Figure 5 supports the alternative hypothesis. The correlation coefficient of the average DOX series and the recursively estimated predictability coefficient series is approximately 80%, and is statistically significant at the 1% level.

A more formal test of the relation between the coefficient of predictability $\widehat{\beta_{RW_m}}$ and the average degree of extrapolation bias $\overline{DOX_{RW_m}}$ regresses the former on the latter, with the following result in the case of predictability by the D/P ratio:

$$\begin{array}{llllll} \widehat{\beta_{RW_m}} = & -\ 21.97 & +\ 68.37 & \overline{DOX_{RW_m}} + \epsilon_m & & R^2 = 69\% \\ & [-6.87] & [9.12] & & & \end{array}$$

where Newey-West (1987) t-statistics with 12 lags are reported in brackets.[26] The result above suggests that when the average in-sample DOX grows by 10%, the coefficient of predictability increases by seven units. Additionally, an average DOX of 0.3 or above is necessary to turn the coefficient of predictability positive. This threshold is broadly consistent with the content of Table 5, in which it can be seen that the conditional coefficient of predictability, $b_0 + b_1 DOX$, becomes positive for a DOX between 0.3 and 0.45, depending on the combination of price-scaled variable and survey being selected. Additionally, time-series variation in average DOX accounts for

[26]We also performed an ARIMA analysis of the regression residuals and performed inference with a longer lag size of 24 months. Inference is unchanged.

approximately 69% of time-series variation in the predictability coefficient. Similar results apply to the use of B/M and E/P, as Panel B and Panel C of Figure 5 confirm. Consequently, it appears that the documented time-series variation in the ability of price-scaled variables to predict future returns can be explained with time-series variation in investors' degree of extrapolation bias.

5.6 Out-of-sample results

In this section, we investigate whether the in-sample evidence on the conditioning role of extrapolators' DOX for stock return predictability is confirmed out-of-sample. Consider the three forecasting models M_0, M_1, and M_2 defined below:

$$
\begin{aligned}
M_0 &: R^e_{t_0,t_0+l} = \mu_{t_0} + \epsilon^{M_0}_{t_0,t_0+l} \\
M_1 &: R^e_{t_0,t_0+l} = a_0 + b_1 \frac{D}{P}_{t0} + \epsilon^{M_1}_{t_0,t_0+l} \\
M_2 &: R^e_{t_0,t_0+l} = (a_0 + a_1 DOX_{t0}) + \frac{D}{P}_{t0}(b_1 + b_2 DOX_{t0}) + \epsilon^{M_2}_{t_0,t_0+l}
\end{aligned}
$$

M_0 is the naive forecasting model that uses the historical average excess return as a forecast of the future return. M_1 is the univariate prediction specification addressed by Goyal and Welch (2008), who document its poor performance in pseudo out-of-sample tests. M_2 is the augmented forecasting specification that is the focus of this study. In what follows, we concentrate on out-of-sample prediction of excess returns at a quarter and a year horizon. We perform an out-of-sample pairwise comparison of any two models M_i and M_j in three ways. First, we follow Clark and West (2007), who develop a one-tailed test of equal predictive accuracy of nested linear specifications well-suited for our case. To implement the Clark and West test for a forecasting horizon l, every month m we estimate each of the models using all observations available between the date of the first DOX estimate and m. We then use the estimated coefficients in conjunction with the value of the right-hand-side variables in month *(m+l)*, to forecast excess returns over the interval *(m+l,m+2l)*. The first out-of-sample month is 1997:06, so as to allow a five-year period for the first in-sample parameter estimation. Clark and West's test statistic for comparing model M_i and M_j is the intercept obtained by regressing $[2FE^i_{m+l}(FE^i_{m+l} - FE^j_{m+l})]$ on a constant. This regression-based approach allows us to produce standard errors that are corrected for heteroskedasticity and serial correlation. The latter is a concern when $l > 1$.

In Panel A of Table 7, we compare models M_i and M_j ($M_i vs M_j$) and test the one-sided null hypothesis of equal prediction accuracy of M_i and M_j versus the alternative of higher accuracy of model M_j. A positive value of the statistic suggests that M_j fairs better than M_i. As in prior literature, we find that the standard univariate prediction model never beats the historical average in a statistically significant way. As for the conditional prediction model M_2, the results confirm that it provides better prediction accuracy than its univariate counterpart. In all but one case, the improvement in forecasting accuracy is always statistically significant at least at the 5% level. Additionally, the conditional model also provides a statistically significant accuracy improvement over the naive forecast.

The next piece of out-of-sample evidence is based on the out-of-sample R^2 proposed in Campbell and Thompson (2008) and Rapach, Strauss, and Zhou (2010). It is calculated as follows:

$$R^2_{OOS_{M_i vs M_j}} = 1 - \frac{\sum_{t=m_0}^{T} [(r_{t,t+l}) - r_{t,t+l}^{\hat{M_j}}]^2}{\sum_{t=m_0}^{T} [(r_{t,t+l}) - r_{t,t+l}^{\hat{M_i}}]^2} \tag{11}$$

where $r_{t,t+l}$ is the ex-post l-months cumulative returns in the interval (t,t+l), and $r_{t,t+l}^{\hat{M_j}}$ is the out-of-sample (OOS) prediction of model Mj,. When $R^2_{OOS_l M_i vs, M_j}$ is positive, M$_j$ fares better relative to model M$_i$. When $R^2_{OOS_l M_i vs, M_j}$ is close to 0, M$_i$ and M$_j$ have comparable OOS performance. Negative values of the statistic point to a decline in accuracy when migrating from M$_i$ to M$_j$. Panel B of Table 7 presents results of pairwise (i, j) comparison. Results confirm prior findings on the weak ability of univariate forecasting models to subsume the historical average. The OOS R^2 statistic is approximately 1%. At the same time, with one exception, the DOX-based conditional model outperforms both the historical average and the univariate model.

Next, we measure the economic gains introduced by using M_2 instead of M_1, or M_0. One approach is to quantify the economic gains reaped by an expected utility maximizer when she moves from the traditional univariate forecasting models M_1, or the naive forecast M_0, to the conditional model M_2. To accomplish this, we follow Campbell and Thompson (2008) and solve for the optimal portfolio allocation of a rational investor who lives for only one period. Her portfolio includes two assets: a risk-free and a risky asset that proxies for the aggregate market. We assume power utility with a coefficient of relative risk aversion of 3, which is consistent with the estimation in Friend and Blume (1975). At the end of month m, the portfolio share of the risky asset is given by:

$$w^r_{m,M_j} = \frac{1}{3}\frac{(r_{m,m+l}^{\hat{M_j}})}{\sigma_\epsilon^{2^{M_j}}} = \frac{(r_{m,m+l}^{\hat{M_j}})}{3\sigma_r^2(1 - R^2_{m_0,m}{}^{M_j})} \tag{12}$$

where $r_{m,m+l}^{\hat{M_j}}$ is the model-dependent forecasted excess-return for the period *(m,m+l)*, $\sigma_\epsilon^{2^{M_j}}$is the conditional excess-return variance that characterizes model M$_j$, and $R^2_{m_0,m}{}^{M_j}$ is model M$_j$ in-sample goodness of fit until month m. Intuitively, when a rational investor expects a higher reward per unit of risk, she will invest more in the risky asset. Similarly, when a model reduces conditional uncertainty $\sigma_\epsilon^{2^{M_j}}$, the risk perceived by the investor decreases, and she invests in a risky asset more aggressively.

To make our scenario more realistic, we impose two boundary constraints on w^r_{m,M_j}. The lower boundary of 0 is set because a forecast of negative excess-returns is challenged on economic grounds, while the upper boundary of 1.5 sets a limit to the investors' leverage. For each model

M_j we calculate investor's average ex-post annualized utility:

$$U^{\bar{M}_j} = \left(r_{p,l}^{\bar{M}_j} - \frac{3\sigma_{p,l}^2}{2} \right) \frac{12}{l} \tag{13}$$

where $r_{p,l}^{\bar{M}_j}$ and $\sigma_{p,l}^2$ represent the investor's ex-post average portfolio return and portfolio return variance, respectively. Panel C of Table 7 presents the comparative results for the three models. In line with the first two pieces of OOS evidence, the ex-post average utility improvement calculation reveals that forecasting with the dividend-price ratio does not lead to a large ex-post utility improvement compared to the use of the naive forecast, and in some instances the agent is actually slightly worse off. The conditional model always beats both the naive and the univariate model, with an annualized ex-post utility improvement between 3% and 10%.

To make the achieved economic benefits easier to interpret, we report the agent's portfolio mean return and Sharpe ratio under each model. The evidence is overwhelmingly in favor of the conditional model M_2. For example, when moving from the univariate prediction model to the conditional one, the agent usually sees an annualized mean return improvement between 3% to 5%. Moreover, while the conditional model always subsumes the naive forecast, the univariate model does so only when B/M and E/P are adopted, and the improvement is between 1% and 4%. A further comparison with respect to the portfolio Sharpe ratio confirms the superiority of the conditional model over the univariate and naive ones. For instance, using the D/P as a univariate predictor and focusing on the 3-month prediction horizon, the Sharpe ratio moves from 0.21 when the naive forecast is adopted, to 0.26 with the univariate model, and results in a 60% improvement when the conditional model is used, since it increases to 0.41. The wedge between Sharpe ratios increases at a yearly horizon, in which both the univariate and the historical average have Sharpe ratios of approximately 0.15, compared to 0.43 for the conditional model.

As a final measure of the wealth effects of moving from simple forecasting models to the conditional one that is our focus, we present in Panel D of Table 7 the results of a terminal wealth calculation: the expected utility maximizer modeled above is endowed with \$100 in the month 1997:06. The investor rebalances her portfolio every three or 12 months, and on each such occasion, she uses either M_0, M_1, or M_2 to choose optimal portfolio weights. Terminal wealth is calculated as of the final out-of-sample forecast. Once again, the results point to the benefit of adopting the conditional model M_2 over the unconditional M_1 and the naive forecast M_0. Across predictors and horizons, the gain in investor's final wealth due to the conditional model ranges from 7% to more than 100%. Results are particularly strong with the B/M ratio, and at the 12-month horizon. In unreported tests, we further compare the terminal wealth amounts with those of a buy-and-hold strategy. We find that a buy-and-hold investor would have earned \$340, and therefore would have been ex-post better off than a forecaster who adopted the naive or univariate prediction model. Nevertheless, a buy-and-hold strategy would have been subsumed by the conditional model, which earned on average across predictors and horizons, \$410, a 20% improvement. In summary, out-of-sample results support our in-sample inference, and reject the null hypothesis of the no conditioning role of investors' degree of extrapolation bias for stock return predictability by price-scaled predictors.

6 Robustness

In this section, we perform additional robustness tests. For brevity, we discuss results here but report the related tables and figures in the Appendix.

6.1 Fixed-window DOX estimation

In order to estimate the degree-of-overextrapolation time-series, we have used a dynamic window combination. We now replace it with a fixed window length. In an effort to balance estimation efficiency and bias, to reduce the chance of detecting spurious variation in the model underlying parameters, and to capture time series variation in DOX in a timely manner, we choose 36 months as a fixed window size. At the end of month m, we estimate Equation 6 using monthly observations in the interval *[m-36+1,m]*, and we assign the estimated DOX to month m. Subsequently, we reestimate Equation 7 and Equation 9. Tables A1 and A2 confirm that our in-sample results are still valid using a simpler estimation methodology for the DOX. Table A3 replicates out-of-sample evidence and again confirms the findings discussed above.

6.2 Predicting raw returns, capital gains, log returns

In Table A4 we show that our stock return predictability results can be extended to the forecast of the raw return and capital gain components of stock market returns, as well as to the use of log excess returns. Raw returns are relevant, since the present-value identity used as a motivating econometric tool in Section 3 relates the dividend-price ratio directly to total returns, not risk premia. The capital gain component of returns is of interest, because in our study, stock return predictability is the consequence of an initial irrational rise in index prices, which is eventually corrected when extrapolators' beliefs are adjusted. Finally, we predict log excess returns, since prior literature on stock return predictability uses log-transformations of the right and left side variables in the predictive regression. We present results for a representative prediction horizon of 12 months, but similar conclusions are obtained for other time spans. A comparison between Table A4 and the earlier in-sample results of Table 5 reveals a remarkable similarity between coefficient estimates and goodness of fit across tables. Table A4 also confirms that our results are robust to the use of logarithms in our predictive regression.

6.3 Competing state variables

We next aim to document the robustness of our conditional predictability results to the inclusion of other potential state variables. To this end, we consider a set of k sources of conditional stock return predictability, which include our degree of overextrapolation variable, and extend our earlier specification in Equation 7 as follows:

$$R_{t,t+l} = (A'Z_t) + D/P_t(B'Z_t) + \epsilon^R_{t,t+l} \tag{14}$$

where A and B are two (k+1)×1 vectors of coefficients, whose first row corresponds to the unconditional coefficient a_0 and b_0 in Equation 7, and Z_t is a (k+1)×1 vector of potential state variables in the predictive regression, which includes the constant 1 in its top row, and stacks all the k state-variables, including the DOX, in the remaining rows. The competing state variables we consider are: quarterly returns, the Baker and Wurgler's (2006) measure of investor sentiment, growth in industrial production, and the NBER recession indicator.[27] If the DOX proxies for reversal of extreme realizations of the return on the stock market, controlling for the most recent quarterly returns should largely attenuate its marginal effect on predictability. Controlling for the Baker and Wurgler (2006) sentiment is important, given its prominence in the literature as a market-based proxy of investors' beliefs and dispositions, as well as its documented ability to predict future stock market returns (Baker, Wurgler, and Yuan (2011) and Huang et. al (2014)). Including state variables that capture the business cycle is key, given the evidence in recent literature, which ties time-varying predictability to the state of the economy and to countercyclical risk premia (Henkel, Martin, and Nardari (2011), and Dangl and Halling (2012)). We initially run conditional regressions which feature only one of the competing state variables mentioned above. We then choose k=2, as we horse race our DOX with any one competing source of conditional predictability. Finally, we perform a kitchen-sink regression in which all the competing state variables are included in the model. Table *A5* reports the results for the 12-month prediction horizon, and the use of the dividend-price ratio. In each of the pairwise comparisons, the coefficient on the interaction term of D/P and the DOX is significant and subsumes the competing state variable. Furthermore, in the kitchen-sink regression, the DOX beats all the others proposed state variables combined, and none of the competing interaction terms is significant. This is evidence that that DOX captures the most relevant source of variation in the predictability relation. Results are similar when we use other price-scaled variables.

To further confirm the robustness of the DOX to the inclusion of other competing state variables, we replicate the evidence presented in Section 5.5, and replace the DOX with the NBER recession dummy, and with log growth in industrial production. In Figure *A1* we show, in Panel B, that there is indeed a positive relation between the occurrence of economic contractions during the sample period, and the observed stock return predictability during that same period. The extent of the relation is stronger in the early portion of the sample period, while the association between number of recessions and predictability becomes less strong towards the end of the sample. In Panel A, we show evidence the relation between cumulative industrial production growth and predictability. A more formal test of the relationship between predictability and potential state variables is presented in Table *A6*. The table shows that the presence of recessions in the sample period over which stock

[27]Sentiment is from Jeffrey Wurgler's website (http://people.stern.nyu.edu/jwurgler). Growth in industrial production and the NBER recession indicator are from the Federal Reserve Bank of Saint Louis.

return predictability is assessed is positively correlated with the extent of predictability, as found in prior literature. This lends support to a theory that relates predictability to time-varying risk premia. Nevertheless, the variation in the predictability coefficient explained by this state variable is less than 2% of the overall observed variation in the predictability coefficient. A slightly higher variation is matched by cumulative growth in industrial production, which exhibits the wrong sign, however. Finally, in a specification that includes the DOX as a state variable, almost all the observed time-series variation in the predictability coefficient is accounted for, and the DOX is the strongest explanatory variable in statistical terms.

6.4 DOX falsification tests

We then perform a falsification test that addresses the concern voiced by Lamont (2003) and Cochrane (2011) that surveys are a noisy proxy for investors' beliefs. If this is the case, estimating the model of extrapolation in Equation 6 equates to overfitting, and the DOX time-series we estimate is noise. Using Monte Carlo simulations, we generate 50000 fictitious DOX sequences, whose values lie between 0 and 1, and whose mean and variance match the mean and the variance of the DOX extracted from the principal component (PC) of the II and AA surveys. For each artificially created DOX series, we estimate our conditioning predictive model 7 and draw an empirical distribution of the regressions coefficients. Finally, we place our actual coefficient estimates presented in Table 5 on the empirical distribution so as to have an indication of the likelihood of obtaining our results if the DOX were pure noise. Results in Figure A2, which refers to the case of stock return predictability by the D/P ratio, reveal two important findings. First, if the DOX were pure noise, the expected coefficient estimate on the interaction (b_1), as well as the coefficient estimate on the DOX (a_1), would be both centered at zero. At the same time, the coefficient estimate on the D/P (b_0) would be centered around the value we estimate in our baseline regressions in Table 5. Second, if the DOX were pure noise, it would never deliver coefficient estimates as extreme as those we present in our sample results, since the actual coefficients estimated always lie far from the empirical distribution. We obtain similar results for B/M and E/P. These results point to the informativeness of survey data, and confirm the information content of our DOX measure.

6.5 Persistent price-scaled predictors and small sample bias

One potential concern in our main conditional regression framework of Equation 7 is that persistence in the price-scaled predictors may generate our conditional regression results spuriously. As a first step towards addressing this possibility, in unreported tests we add a time trend interacted with the DOX to our main specification in Equation 7. We find that doing so alters neither the magnitude nor the statistical significance of our coefficient of interest on the interaction term.

Next, we study the finite-sample implications of persistence in the price-scaled predictors. Nelson and Kim (1993), Stambaugh (1999), and Campbell and Yogo (2005) among others, show that while OLS estimates of the predictability coefficient are asymptotically consistent under standard conditions, they may be biased in a small sample. The bias increases when the predictor is highly autocorrelated, and when the predictor and predicted variable are highly contemporaneously correlated. The small sample bias is particularly relevant in the context of this paper, because of the high persistence of price-scaled variables, as well as the high mechanical negative correlation between innovations in predictors and innovations in returns. Our framework is fundamentally different from the simple univariate case. The presence of other covariates, as well as the posited conditional nature of the autocorrelation coefficient of the predictor variable, does not allow us to adopt the closed-form measure of the bias in Stambaugh (1999). Therefore we resort to bootstrapping techniques. To this end, we follow the procedure in Baker, Taliaferro, and Wurgler (BTW, 2006) and adapt it to the null hypothesis of no conditioning role of the DOX in the predictive regression. Like BTW, we first run OLS regressions under the null hypothesis. We present two alternative null models that differ in the econometric specification of the predictor variable. In the first model (${H_0}^1$), we estimate the following return and predictor equations:

$$
{H_0}^1 : \qquad \begin{cases} R^e_{t,t+12} & = (a_0 + a_1 DOX_t) + b_0 D/P_t + \epsilon^r_{t,t+12} \\ \mathit{Predictor}_{t+12} & = (\alpha_0 + \alpha_1 DOX_t) + \mathit{Predictor}_t (c_0 + c_1 DOX_t) + \epsilon^P_{t,t+12} \end{cases} \tag{15}
$$

where we treat the DOX as non-stochastic. To avoid the complications that may arise due to overlapping observations, we run annual regressions. At the same time, in order to use all available information, we run 12 separate sets of such annual regressions, one for each possible year-end. As in BTW, the estimated error terms are measured after correcting for known sources of bias in the OLS coefficient estimates. In particular, we correct for the Kendall (1954) bias in the estimation of the AR(1) coefficient c_0, as well as for the Stambaugh (1986) bias in the estimation of the coefficient of predictability b_0, via a first round of Monte Carlo simulations.[28] We use the bias-corrected estimates of the coefficient in the null system of equations ${H_0}^1$ to construct a joint empirical distribution of disturbance terms $(\epsilon^r_{t,t+12}, \epsilon^P_{t,t+12})$. Subsequently, we draw with replacement from the joint empirical distribution of the errors to create 10000 artificial pairs $(R^{e*}, \mathit{Predictor}^*)$ consistent with the null of no conditional stock return predictability. Using the artificially created series, we then estimate the return equation:

$$
{R^{e*}}_{t,t+12} = (a_0 + a_1 DOX_t) + {\mathit{Predictor}_t}^* (b_0 + b_1 DOX_t) + \epsilon^R_{t,t+12} \tag{16}
$$

which is identical to the one used in our main test in Table 5. We collect the simulated coefficient estimates of interest ${b_1}^*$ from each year-end regression, and aggregate them into a unique empirical distribution of 120000 estimates. Results are presented in Panel A, where we report the overall average of the coefficient estimates (E[${b_1}^*$]), the actual coefficient estimate (b_1) from Table 5, the

[28]Under a simple AR (1) model, Kendall (1954) has shown that there is a small sample bias in the estimate of a process autocorrelation coefficient. Additionally, OLS coefficient estimates in the return null equation suffer from the Stambaugh (1986) bias. Through simulations we find, as expected, that the AR (1) coefficient c_0 suffers from downward bias. We also find downward bias in estimate of the coefficient on the interaction term, but it is small. Similarly, there is large upward bias in the coefficient estimate of the predictive coefficient b_0. Correcting the bias reduces the coefficient by approximately 50%.

ratio of the average simulated coefficient estimate to the actual estimate ($\mathrm{E}[{b_1}^*]/b_1$), and the one-sided empirical probability of obtaining, under the null, a coefficient ${b_1}^*$ that is of the same sign and as large as our actual one b_1.

In Panel B, we report simulation results for a second setting (${H_0}^2$), in which we acknowledge the joint nature of our hypothesis of conditional stock return predictability, and accordingly modify the null hypothesis in Equation 15, by imposing the further restriction $c_1 = 0$.

The results in both panels of Table A7 show that the amount of the bias in the coefficient b_1 on the interaction term is small, accounting on average for approximately 5% of our full sample estimate. Additionally, consistent with prior findings on size distortions in predictive regressions, the one-sided p-values confirm that using traditional standard thresholds for inference on the statistical significance of the interaction coefficient may indeed lead to over-rejection. Nevertheless, our bootstrapped p-values support our main findings, since on average the full-sample estimate of the coefficient on the interaction term is larger than 94% of the simulated coefficient estimates obtained under the null. Using B/M and E/P as predictor variables allows us to reach the 5% statistical significance mark, while the the null hypothesis is rejected at the 10% level when the D/P is used. In unreported results, we also perform an empirical test of the joint null that the interaction coefficients in both the predictor and return equation are 0 ($H_0 : b_1 = 0, c_1 = 0$). We find that the joint null is rejected with a size of 3%, thereby supporting the statistical significance of our main findings.

In summary, this section shows that our main results i) are robust to changes in the DOX estimation methodology, ii) are valid for the prediction of the raw returns and capital gains, iii) are robust to the inclusion of other competing state variables that proxy for countercyclical risk premia and investor sentiment, iv) would not arise if the DOX held no information content, and v) do not arise spuriously due to the known small sample bias that affects estimation in predictive regressions.

7 Conclusion

The evidence of time-series predictability of stock returns by price-scaled variables goes back more than 30 years. While there is a considerable amount of research that attributes predictability to time-series variation in required returns set by rational agents, less has been done to evaluate the extent to which irrational beliefs result in predictable patterns in stock returns. Motivated by the recent works of Greenwood and Shleifer (2014) and Barberis, Greenwood, Jin, and Shleifer (2015), we investigate how one such bias, overextrapolation, can explain the relationship between price-scaled variables and future stock returns.

In this study, we use survey data to measure a degree of extrapolation bias (DOX) in investor expectations of stock market returns in the US. We argue ex-ante that the DOX is time-varying in nature. Through a recursive estimation methodology, we confirm our intuition and document considerable time variation in the DOX. We subsequently show that the predictability of the equity premium by price-scaled variables is contingent on the DOX. In particular, the relation between the D/P, the B/M, or the E/P ratio and future returns is positive and significant in economic and statistical terms when the DOX is high, while the predictability becomes weaker when the DOX is low, and the sign of the predictive relation turns from positive to negative. Furthermore, consistent with the intuition from the Campbell and Shiller (1988) present-value identity, we link the evidence of conditional stock return predictability to conditional mean-reversion in the price-scaled predictors. Specifically, we find that states of high DOX and stronger stock return predictability are associated with quicker mean reversion of price-scaled variables. Conversely, these price-ratios are much more persistent in states of low DOX, and such persistence weakens their ability to predict future returns. Finally, we reconcile evidence of parameter instability in predictive regressions in which price-scaled variables are used to predict future returns. We show that by accounting for time-series variation in the DOX, we are able to explain approximately 70% of the witnessed variability in the coefficient of predictability. These results are confirmed both in and out of sample, extend to the prediction of raw returns and capital gains, and are robust to the inclusion of other potential state variables from both the behavioral literature and the literature on time-varying risk premia.

Our findings have important implications. Our results lend support to the hypothesis that price-scaled variables do not only proxy for time-varying risk premia, but also capture the degree of mispricing in the stock market. More importantly, our study addresses an age-old question, namely when will an overvalued asset correct back to fair value? We entertain the possibility that extrapolative beliefs are responsible for aggregate stock market misvaluation, and further hypothesize that if this is the case, mispricing should be corrected more quickly when extrapolative beliefs are more transitory i.e. when DOX increases. Our conditional regressions provide results that are consistent with this conjecture. Furthermore, our specification delivers accurate negative equity premium predictions. This is difficult to reconcile with traditional models of risk in which expected and required returns coincide, and therefore expected equity returns can never be lower than the risk-free rate. Overall, our evidence suggests that DOX can be interpreted as a market-timing device which complements information on the existence of mispricing contained in the aggregate D/P, B/M, and E/P ratio.

While this new evidence in favor of a behavioral explanation of return predictability speaks to the specific effect that extrapolation may have on prices and their dynamics, there is still much to examine. Finding evidence of extrapolation does not necessarily mean that the required compensation for risk remains constant during the business cycle, and the nature of the interplay between these two features has not been studied. Furthermore, extrapolation is one of many known behavioral biases which may contribute to the rise and fall of fads. Entertaining richer expectation dynamics may prove useful in understanding asymmetric phenomena such as booms and busts. Finally, this study focuses on demand-side extrapolation, and leaves the issue of how extrapolation can affect the supply-side of the equity market for future research. There is evidence, such as that presented by Baker and Wurgler (2000) and Greenwood and Shleifer (2014), that corporations in the aggregate understand mispricing and use it to their advantage. On the other hand, a recent paper by Gennaioli, Yueran, and Shleifer (2015) argues that at a micro-level, decision makers within corporations are prone to making mistakes similar to those traditionally attributed to less sophisticated investors. How supply and demand-side extrapolation jointly generate equilibrium prices is a question for future research.

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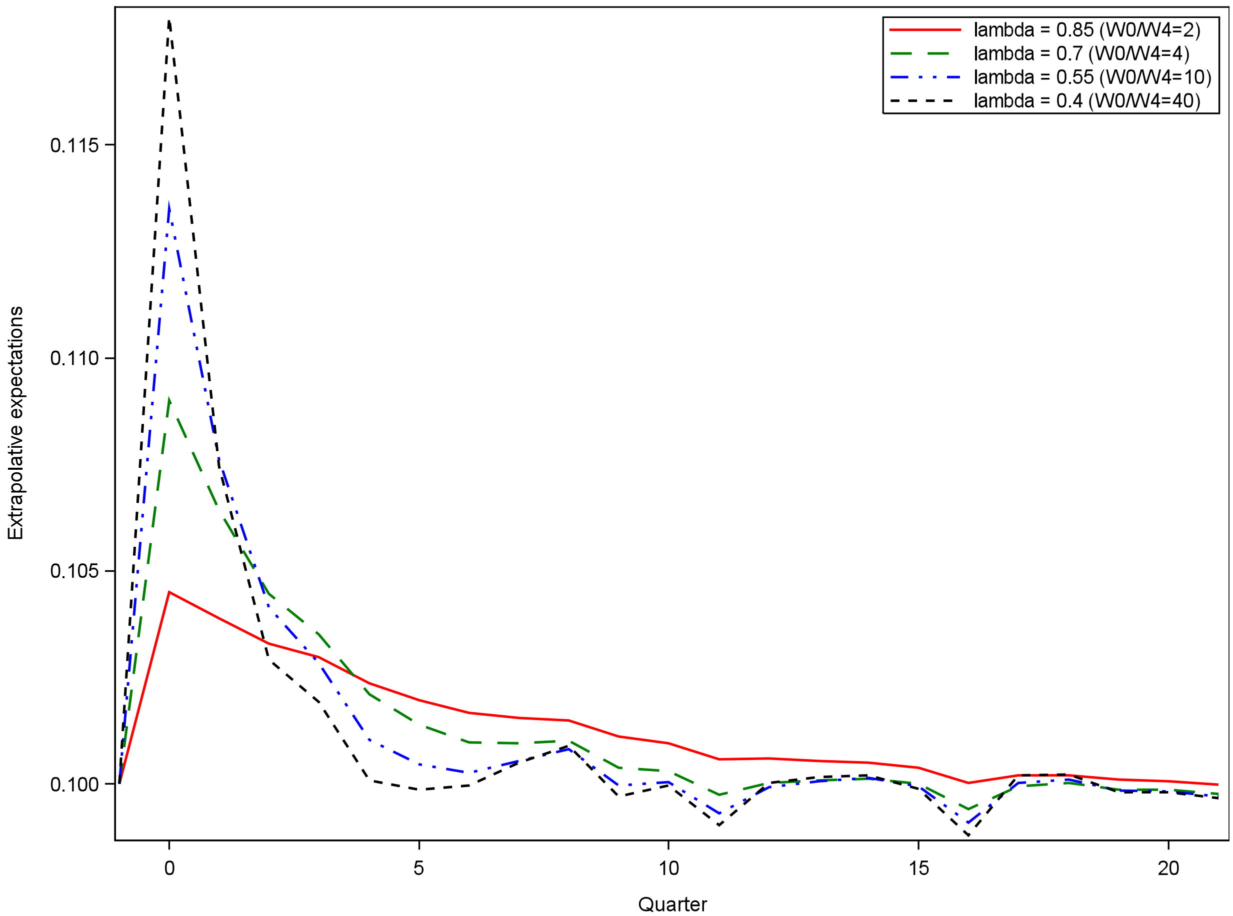


Figure 1
Time series behavior of extrapolative beliefs
We model extrapolative beliefs as an infinite summation of current and past quarterly return realizations, as in Equation 6. Assume that at the end of quarter t=-1 extrapolators' expectations are at their long-run mean value of about 10%. At time $t = 0$, a quarterly return of 5% is realized and incorporated into expectations. We then report the average value of extrapolators' expectations in t $\in$ [1,20], obtained by simulating 5,000 time-series of subsequent returns. Such returns are generated by matching mean and variance of the historical quarterly returns of the CRSP value-weighted portfolio in the period 1987–2014. We report the resulting pattern in extrapolators' expectations for four values of the smoothness parameter λ, 0.85, 0.7, 0.55, and 0.4, which correspond to a relative weight of current quarterly returns versus quarterly returns the previous year of 2, 4, 10, and 40, respectively.

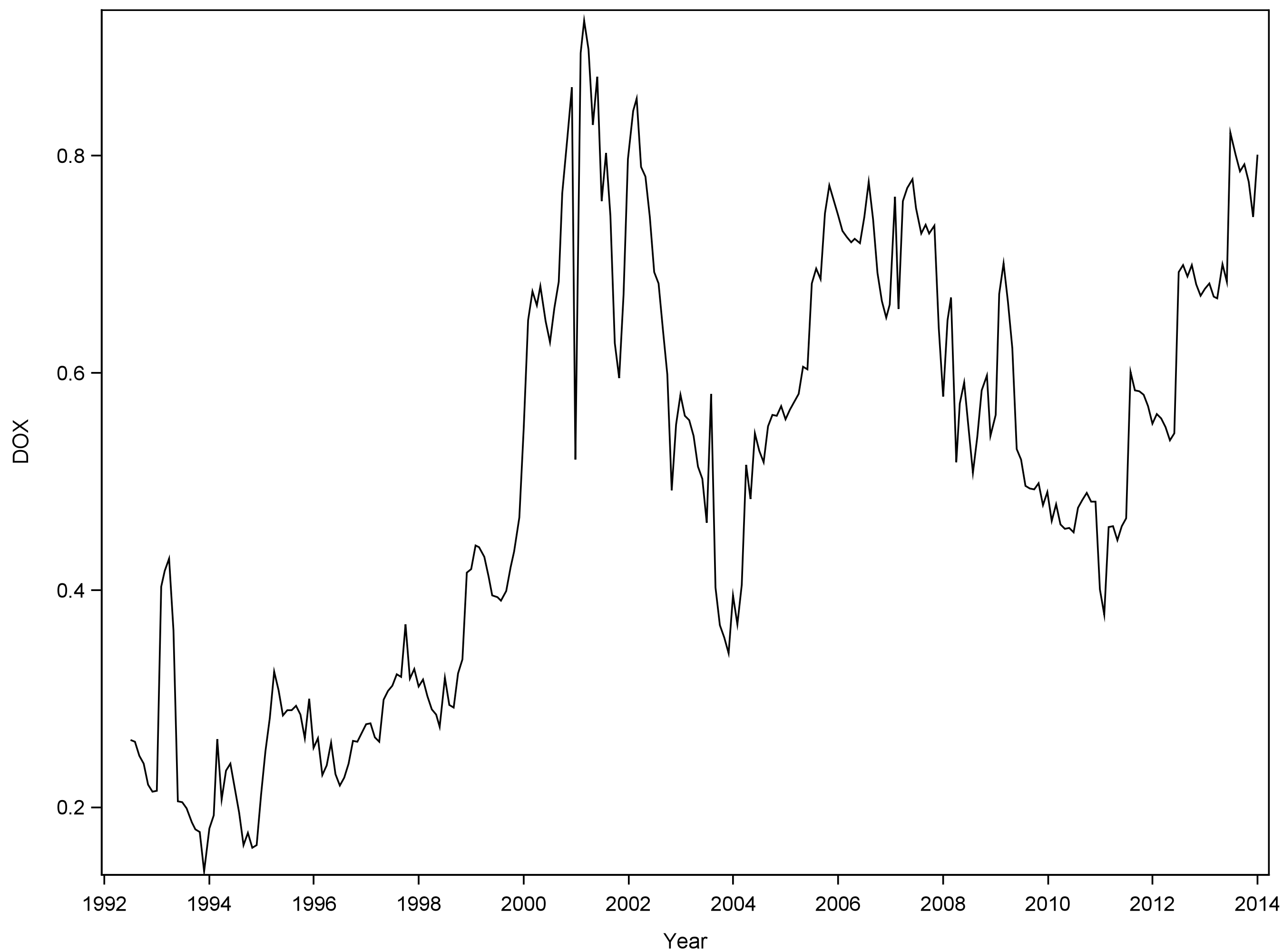


Figure 2
Time-varying degree of extrapolation bias

The figure plots the recursively estimated DOX time-series for the principal component (PC) of the II and AA surveys, in the 1992:06–2014:12. The reported time-series is obtained via dynamic window selection. (Details are in Section 3.)

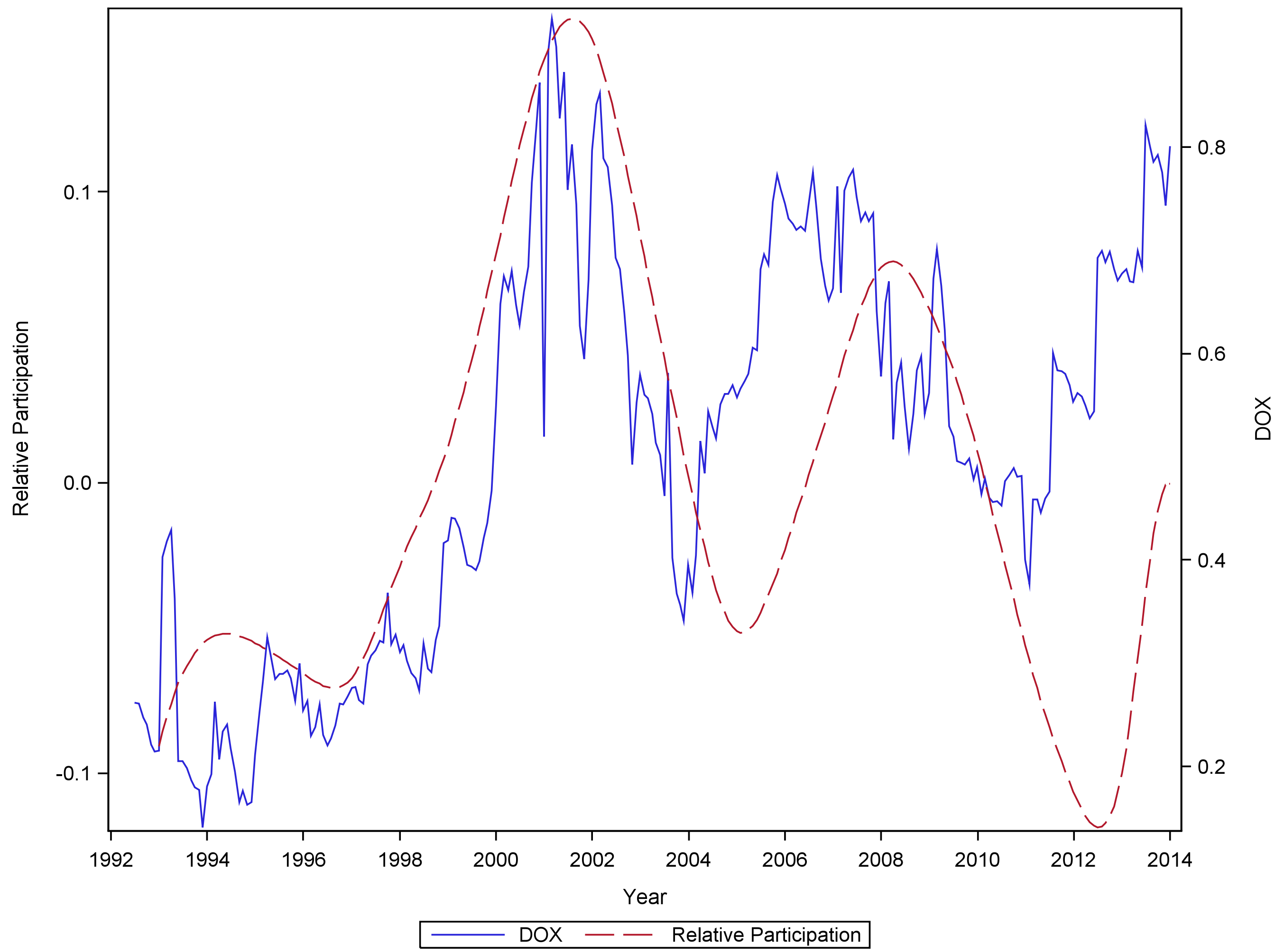


Figure 3
DOX and the relative participation of Young and the Old in the stock market
In the sample period 1992:06 - 2013:12, we recursively estimate the degree of overextrapolation coefficient (DOX) from survey data. During the same period, we report the detrended relative participation of the Young versus the Old in the stock market. (Details on series construction can be found in section 5.2).

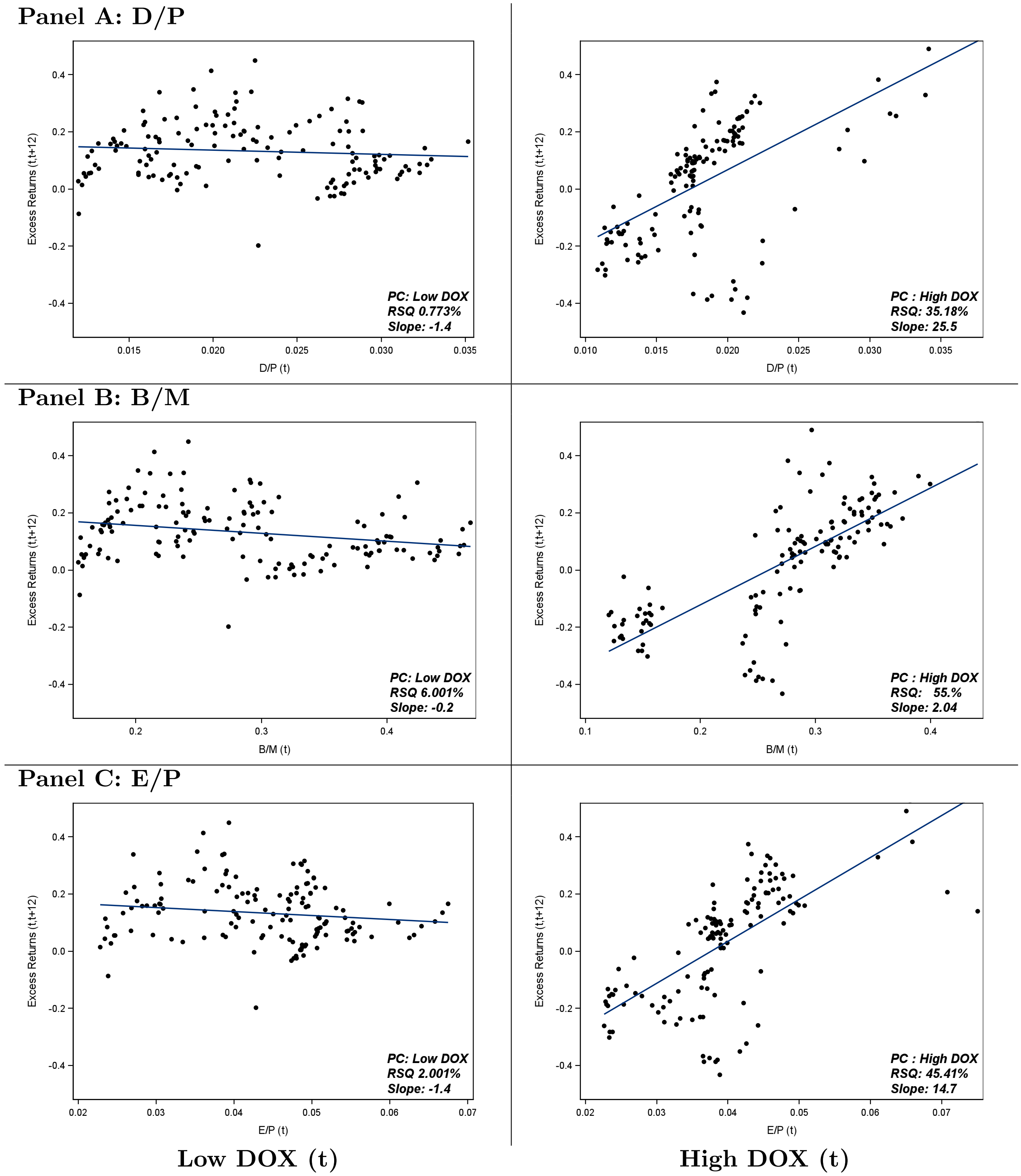
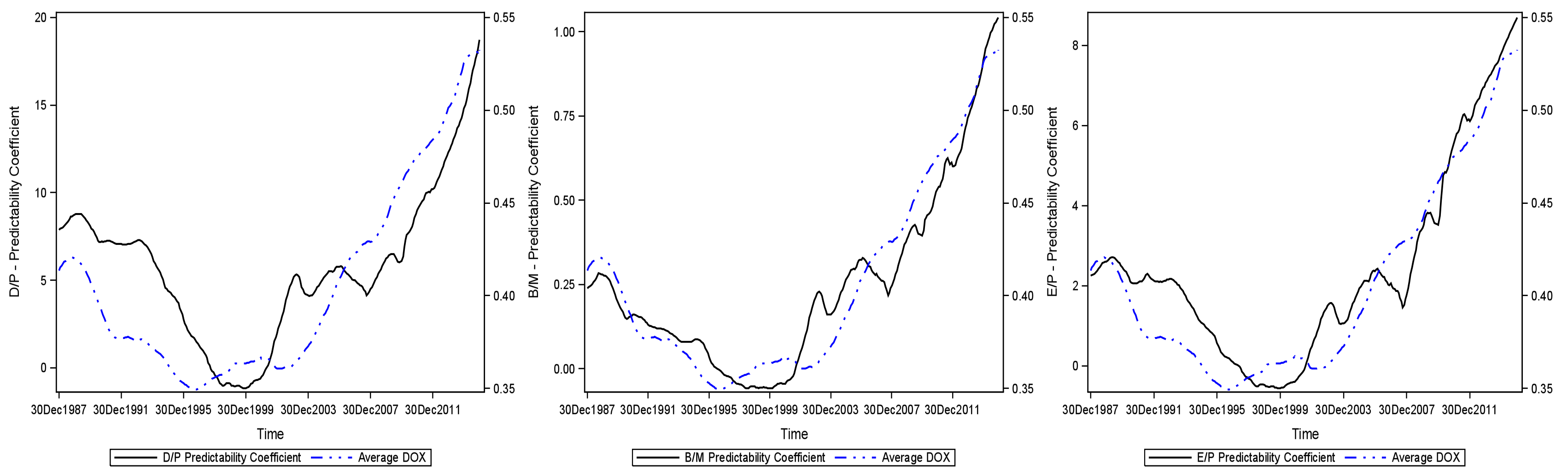


Figure 4
Conditional stock return predictability
In the period 1992:06 to 2013:12, we classify each month m based on the degree-of-overextrapolation (DOX) extracted from the principal component (PC) of the II and AA surveys. The left panel reports a scatter plot of the relationship between the D/P ratio (Panel A), the B/M ratio (Panel B), and the cyclically adjusted E/P ratio (Panel C) in month m and the subsequent 12 stock market excess returns, when the DOX in month m is low (i.e. below its median value of 0.51). The right panel reproduces a similar scatter plot for the months in which the DOX is high (i.e. above the median). Each figure also reports R^2 and coefficient of predictability of the corresponding univariate predictive regression.



Panel A: D/P Panel B: B/M Panel C: E/P

Figure 5
Stock return predictability: parameter instability

In the sample period 1967:12–2013:12, we run univariate predictive regressions of one-year-ahead excess returns on current D/P ratio (Panel A), B/M ratio (Panel B), and cyclically adjusted E/P ratio (Panel C), over a rolling window of 20 years. At the same time, we construct a 20-year moving average degree of overextrapolation time-series, using the PC_{ext} DOX time-series. The solid line reports the recursively estimated univariate coefficient of predictability, and the dashed line reports the moving-average DOX.

Table 1
Summary statistics

This table presents summary statistics. Panel A reports general information on the surveys of investor expectations in our analysis. *II* is the Investor Intelligence survey of US financial advisors' newsletters. *AA* is the survey conducted by the American Association of Individual Investors. *PC* is the principal component of AA and II. *Gallup ER* is a version of the UBS\Gallup survey that elicits quantitative forecasts of future returns. Panel B reports summary information for the other time-series used in this paper. *D/P* is the aggregate dividend-price ratio on the *S*&P500. *B/M* is the aggregate Book-to-Market ratio on the DJIA. Both D/P and B/M are from Amit Goyal's website. *E/P* is the aggregate cyclically adjusted earnings-to-price ratio on the S&P500, from Robert Shiller's website. Excess return is constructed by subtracting the risk-free rate from the total return on the CRSP value-weighted portfolio of US stocks. The monthly return on US treasury securities is used as risk-free and is from Ken French's website. In Panel A and Panel B $\rho(l)$ is the l-months autocorrelation and σ is the unconditional volatility. Panel C shows pairwise correlations between the time-series used in the paper.

Panel A: Survey general information

Survey	**Period**	N	**Mean**	**Median**	**Minimum**	**Maximum**	σ	$\rho(3)$	$\rho(12)$	**Type**	**Frequency**
II	1963-2014	626	13.63	15.89	-49.2	66.64	19.79	0.56	0.21	Professional	Weekly
AA	1987-2014	331	8.62	9.5	-41	50.47	15.27	0.31	0.17	Retail	Weekly
PC	1987-2014	331	0.00	0.12	-3.87	2.95	1.23	0.44	0.20		Monthly
Gallup ER	1998-2004	54	10.47	10.35	4.5	16.2	3.08	0.84	0.52	Retail	Monthly

Panel B: Other variables

Variable	**Period**	**N**	**Minimum**	**Maximum**	**Mean**	**Median**	σ	ρ_3	ρ_{12}
Excess return (12 months)	1963-2014	623	-0.44	0.53	0.06	0.08	0.16	0.75	-0.04
D/P	1963-2013	612	0.01	0.06	0.03	0.03	0.01	0.97	0.89
B/M	1963-2013	612	0.12	1.21	0.51	0.46	0.27	0.98	0.91
E/P	1963-2013	612	0.02	0.15	0.06	0.05	0.03	0.98	0.91

Panel C: Pairwise correlations

	II	**AA**	**PC**	**Gallup_ER**	**D/P**	**B/M**	**E/P**
AA	0.53 [0.00]						
PC	0.87 [0.00]	0.87 [0.00]					
Gallup_ER	0.46 [0.001]	0.53 [0.00]	0.58 [0.00]				
D/P	-0.35 [0.00]	-0.42 [0.00]	-0.58 [0.00]	-0.81 [0.00]			
B/M	-0.25 [0.00]	-0.38 [0.00]	-0.42 [0.00]	-0.57 [0.00]	0.94 [0.00]		
E/P	-0.16 [0.00]	-0.32 [0.007]	-0.40 [0.00]	-0.83 [0.105]	0.91 [0.00]	0.89 [0.00]	
Excess returns (12 months)	0.49 [0.00]	0.38 [0.00]	0.47 [0.00]	0.85 [0.00]	-0.24 [0.00]	-0.20 [0.00]	-0.12 [0.01]

Table 2
Degree of extrapolation: full sample

The table presents full-sample estimates of the *degree of extrapolation* (DOX) parameter. Specifically, we use nonlinear least squares to fit the following equation:

$$Exp_t = a + b \sum_{j=0}^{59} w_j R^Q_{t-j-1,t-j} + \epsilon_t^{Exp}$$

where Exp_t is the survey-based expectation of future returns, $R^Q_{t-j-1,t-j}$ is the j-lagged quarterly return of the aggregate value-weighted stock market from CRSP, and w_j is a weight parameter whose expression is

$$w_j = \frac{\lambda^j}{\sum_{k=0}^{59} \lambda^k}$$

We then report the corresponding *degree of overextrapolation, (DOX)*, defined as 1-λ, as well as estimates of the center and scale parameters a and b. Coefficients and t-statistics are based on Newey-West standard errors with a lag length of six months. Estimates are presented for II, AA, and their principal component PC. The sample period is 1987:06–2014:12.

Coefficient	AA	II	PC
DOX (1-λ)	0.63	0.50	0.60
	[2.37]	[7.72]	[5.45]
a	5.42	6.92	-0.34
	[3.32]	[3.81]	[-4.78]
b	130.70	238.12	12.59
	[4.85]	[6.78]	[8.02]
Adjusted-R^2	21.90%	30.10%	27.50%

Table 3
Degree of extrapolation: recursive estimation

The table presents summary statistics for the recursive estimation of the *degree of extrapolation* (DOX) parameter. Specifically, every month m we estimate the following model of extrapolative expectations using four alternative window sizes of 24, 36, 48 months, and an expanding window whose starting length is 36 months:

$$Exp_t = a + b \sum_{j=0}^{59} w_j R^Q_{t-j-1,t-j} + \epsilon_t^{Exp}$$

where Exp_t is the survey-based expectation of future returns, $R^Q_{t-j-1,t-j}$ is the j-lagged quarterly return of the aggregate value-weighted stock market from CRSP, and w_j is a weight parameter whose expression is

$$w_j = \frac{\lambda^j}{\sum_{k=0}^{59} \lambda^k}$$

We use month *m-12* to *m-1* as a cross-validation period, in which we assess the one-step ahead mean-squared-forecast-error (MSFE) of our model for each alternative window size. We then calculate a weighted average of the DOX estimates obtained with each window size for month m, where the weights assigned are proportional to the inverse of the MSFE obtained in the cross-validation period. We use the same weights to combine the center and scale parameters a and b. The recursive estimation is conducted for II, AA and their principal component (PC). A recursively estimated DOX is available for the period 1992:06–2014:12. Results are also reported for an extended version of the principal component (PC_{ext}), that uses II-based parameter estimates in the period 1967:12–1992:05, and the PC-based parameter estimates afterwards.

Panel A:DOX (1-λ)

Survey	N	Mean	Median	σ
II	270	0.49	0.51	0.20
AA	270	0.58	0.57	0.20
PC	270	0.49	0.51	0.20
PC_{ext}	564	0.44	0.41	0.20

Panel B: a

Variable	N	Mean	Median	σ
II	270	-10.4	-2.2	29.20
AA	270	2.60	0.7	19.40
PC	270	-1.1	-0.51	1.93
PC_{ext}	564	-7.65	-1.10	17.85

Panel C: b

Variable	N	Mean	Median	σ
II	270	778.5	472.85	765.52
AA	270	411.73	244.27	555.35
PC	270	36.95	22.80	41.45
PC_{ext}	564	36.94	22.80	41.44

Table 4
Potential determinants of the DOX

We run univariate and multivariate regressions of DOX on a set of potential explanatory variables. Data on direct holdings of equities by the Young (*PartRate_Young*, 50 years of age or below) and the Old (*PartRate_Old*, above 50 years of age) is from the Survey of Consumer Finances (SCF). The relative participation of Young to Old (Rel_Participation) is the ratio of number of young to old families with direct holdings of stocks in the US, which is constructed using SCF data, as well as demographic data on households from the US Census. Quarterly return volatility (qRetVol) is measured from daily returns as in French, Schwert, and Stambaugh (1987). Extreme quarter return (ExtrQret) is a dummy variable that tracks quarterly returns that are more than two standard deviations away from the unconditional mean. All variables are detrended. The sample period is 1992:06 -2013:12. Standard errors are robust to heteroskedasticity and serial correlation in errors up to 12 lags.

	(1)	(2)	(3)	(4)	(5)
Intercept	0.001	0.001	-0.025	0.016	0.013
	[0.055]	[0.059]	[-0.926]	[0.655]	[0.564]
Rel_Participation	1.35			1.45	
	[5.492]			[5.741]	
PartRate_Young		0.066			0.072
		[3.431]			[3.747]
PartRate_Old		-0.029			-0.035
		[-1.404]			[-1.707]
qVol			3.762	-1.779	-1.387
			[1.473]	[-1.434]	[-1.221]
ExtrQret			-0.312	-0.039	-0.039
			[-1.709]	[-0.563]	[-0.556]
Adj. R^2(%)	44.37	49.07	3.45	46.24	50.16

Table 5
Extrapolation - Conditional stock return predictability

Using GMM we estimate the following monthly time-series regression of l-month ahead aggregate excess returns:

$$R^e_{t_0,t_0+l} = a_0 + a_1 DOX_{t_0} + D/P_{t_0}[b_0 + b_1 DOX_{t_0}] + \epsilon^R_{t_0,t_0+l}$$

where $R^e_{t_0,t_0+l}$ is the l-months ahead excess return of a value weighted portfolio of US equities from CRSP, the risk-free rate is from Ken French's website, D/P is the aggregate dividend-price ratio, DOX is the degree of extrapolation extracted from II, AA, or their principal component (PC). Panel A reports the results, and includes the univariate predictability regression as a baseline specification. The sample period is 1992:06–2013:12. Panel B and C replace D/P with B/M and E/P, respectively. Coefficients and t-statistics are based on Newey-West standard errors with a lag length of l months. Panel D reports estimates and statistical significance of the one-year conditional coefficient of predictability, $b_t = [b_0 + b_1 DOX_t]$, for the sample period 1992:06–2013:12, and the DOX extracted from the principal component time-series. Standard errors for b_t are constructed following Aiken and West (1991). P-values refer to the one-sided null hypothesis of zero or negative b_t.

Panel A: D/P

Horizon (months)	Coefficient	Baseline	II	AA	PC	
3	a_0	-0.037 [-1.237]	0.248 [2.87]	0.182 [2.88]	0.202 [3.18]	0.006 [0.110]
	a_1		-0.616 [-3.88]	-0.368 [-2.99]	-0.448 [-3.60]	-0.065 [-1.450]
	b_0	2.847 [1.824]	-9.921 [-2.64]	-5.738 [-1.94]	-7.237 [-2.80]	2.250 [1.047]
	b_1		29.315 [3.98]	14.523 [2.18]	19.528 [3.08]	
	$Adj.R^2$	2.9%	12.8%	14.5%	12.8%	5.2%
12	a_0	-0.186 [-1.837]	0.467 [1.74]	0.757 [6.23]	0.694 [5.33]	0.005 [0.035]
	a_1		-1.355 [-2.80]	-1.61 [-8.33]	-1.637 [-7.05]	-0.23 [-1.59]
	b_0	13.654 [2.859]	-14.459 [-1.25]	-26.634 [-4.52]	-23.003 [-3.43]	9.950 [1.96]
	b_1		61.372 [2.63]	69.431 [6.49]	70.264 [5.04]	
	$Adj.R^2$	16.0%	23.0%	49.9%	43.2%	21.9%

Table 5
Extrapolation - Conditional stock return predictability (Continued)

Panel B: B/M

Horizon (months)	Coefficient	Baseline	II	AA	PC	
3	a_0	-0.026	0.204	0.205	0.195	0.013
		[-1.06]	[2.95]	[3.29]	[3.30]	[0.43]
	a_1		-0.458	-0.389	-0.408	-0.083
			[-3.67]	[-4.11]	[-4.20]	[-2.66]
	b_0	0.168	-0.615	-0.512	-0.528	0.180
		[1.95]	[-2.50]	[-2.50]	[-2.64]	[2.07]
	b_1		1.566	1.144	1.275	
			[3.35]	[3.50]	[3.78]	
	$Adj.R^2$	1.6%	8.3%	11.8%	11.5%	6.3%
12	a_0	-0.157	0.57	0.849	0.741	0.021
		[-1.398]	[2.35]	[5.63]	[4.71]	[0.200]
	a_1		-1.43	-1.705	-1.657	-0.327
			[-3.65]	[-6.60]	[-5.04]	[-2.5]
	b_0	0.886	-1.452	-2.319	-1.908	0.830
		[2.545]	[-1.77]	[-5.07]	[-3.43]	[2.88]
	b_1		4.59	5.464	5.114	
			[3.16]	[7.05]	[4.48]	
	$Adj.R^2$	10.6%	26.7%	42.7%	45.4%	27.5%

Panel C: E/P

Horizon (months)	Coefficient	Baseline	II	AA	PC	
3	a_0	-0.061	0.321	0.257	0.255	-0.018
		[-1.946]	[2.82]	[2.94]	[2.78]	[-0.44]
	a_1		-0.766	-0.532	-0.578	-0.06
			[-3.53]	[-3.90]	[-3.67]	[-1.96]
	b_0	1.958	-6.818	-4.752	-5.015	1.78
		[2.706]	[-2.60]	[-2.38]	[-2.47]	[2.26]
	b_1		18.093	11.274	12.919	
			[3.46]	[3.43]	[3.53]	
	$Adj.R^2$	5.0%	14.4%	17.0%	15.5%	8.0%
12	a_0	-0.235	0.69	1.076	0.905	-0.045
		[-1.998]	[1.96]	[5.47]	[4.40]	[-0.37]
	a_1		-1.807	-2.209	-2.075	-0.277
			[-2.99]	[-6.50]	[-5.46]	[-2.04]
	b_0	7.78	-12.442	-21.184	-16.794	6.55
		[3.153]	[-1.53]	[-4.84]	[-3.29]	[3.18]
	b_1		40.083	49.008	45.034	
			[2.65]	[6.45]	[4.72]	
	$Adj.R^2$	15.8%	27.1%	49.2%	46.1%	26.8%

Table 5
Extrapolation - Conditional stock return predictability (Continued)

Panel D: Economic magnitudes

Predictor	DOX	Conditional coefficient $b_t = b_0 + b_1 DOX_t$	t-stat	p-value
D/P	0.31	-1.924	[-0.535]	(0.7)
	0.51	12.128	[3.638]	(0.00)
	0.71	26.181	[5.261]	(0.00)
B/M	0.31	-0.374	[-1.554]	(0.94)
	0.51	0.649	[4.5]	(0.00)
	0.71	1.672	[5.649]	(0.00)
E/P	0.31	-3.284	[-1.384]	(0.92)
	0.51	5.723	[5.282]	(0.00)
	0.71	14.73	[7.381]	(0.00)

Table 6
Price-scaled predictors: conditional mean-reversion

The table reports GMM estimation results for the following monthly conditional autoregressive model:

$$Predictor_{t+12} = a_0 + a_1 * DOX_t + Predictor_t[b_0 + b_1 DOX_t] + \epsilon_t^P$$

The *predictor* variable is one of the following aggregate price-scaled variables: dividend-price (D/P) ratio, the book-to-market (B/M) ratio, or the cyclically adjusted earnings-to-price (E/P). The DOX state variable is extracted from II, AA, or their principal component (PC).The sample period is 1992:06–2012:12. Newey-West t-statistics with six lags are reported in brackets. P-values for the one-sided null hypothesis $H_0 : b_1 \geq 0$ are reported in parenthesis. In Panel B we present the implied half-life of a shock to the predictor in two states: low DOX i.e. (DOX one-standard deviation lower than the median), and high DOX (DOX one-standard deviation above the median).

Survey	Predictor	Panel A: Conditional mean reversion					Panel B: Half life (months)	
		a_0	b_0	a_1	b_1	$Adj.R^2(\%)$	Low DOX	High DOX
II	D/P	0.00 [0.054]	0.926 [3.978]	0.012 [1.059]	-0.571 [-0.907] (0.18)	55.2	29	13
	B/M	-0.03 [-0.534]	0.996 [5.104]	0.256 [2.112]	-0.734 [-1.626] (0.05)	48.4	32	11
	E/P	-0.009 [-0.726]	1.175 [4.281]	0.045 [2.037]	-1.054 [-2.006] (0.02)	50.1	51	10
AA	D/P	-0.01 [-2.837]	1.363 [8.977]	0.028 [3.861]	-1.258 [-3.633] (0.00)	57.5	77	9
	B/M	-0.033 [-0.43]	1.077 [4.094]	0.237 [1.601]	-0.837 [-1.622] (0.05)	41.9	31	10
	E/P	-0.022 [-3.089]	1.365 [7.37]	0.059 [4.403]	-1.164 [-3.308] (0.00)	56.3	122	11
PC	D/P	-0.007 [-2.022]	1.216 [6.757]	0.026 [2.89]	-1.1 [-2.138] (0.017)	55	62	10
	B/M	-0.043 [-0.715]	1.029 [4.852]	0.271 [2.024]	-0.774 [-1.662] (0.05)	44.6	35	11
	E/P	-0.017 [-2.213]	1.271 [6.909]	0.054 [3.645]	-1.079 [-2.846] (0.00)	54.2	127	12

Table 7
Out of Sample tests

The table presents results of out-of-sample test for the following forecasting models:

$$M_0 : R^e_{t_0,t_0+l} = \mu + \epsilon^{M_0}_{t_0,t_0+l}$$
$$M_1 : R^e_{t_0,t_0+l} = a_0 + b_1 Predictor_{t0} + \epsilon^{M_1}_{t0,t_0+l}$$
$$M_2 : R^e_{t_0,t_0+l} = (a_0 + a_1 DOX_{t0}) + Predictor_{t0}(b_1 + b_2 DOX_{t0}) + \epsilon^{M_2}_{t0,t_0+l}$$

The dependent variable $R^e_{t_0,t_0+l}$ is the l-months ahead cumulative excess return. The *Predictor* variable is one of the following: the dividend-price ratio (D/P), the book-to-market ratio (B/M), or the cyclically adjusted earnings-to-price ratio (E/P). The DOX is extracted from the principal component of the AA and II surveys. Starting in 1997:06, every month m we estimate each model using all observations available between the date of the first DOX estimate (1992:06) and m. We use the parameter estimates available in month m and the value of the right-hand variables in month *(m+l)*, to predict the l-months cumulative return over period *(m+l,m+2l)*. We then collect the ex-post forecast errors for each model. Panel A reports Clark and West (2007) one-sided test statistic for the null hypothesis of equal forecasting accuracy of M_i and M_j against the alternative of forecasting improvement of model M_j (Details on can be found in section 5.6). Standard errors are robust to heteroskedasticity and serial correlation with l lags. Panel B presents Campbell and Thompson (2008) measure of out-of-sample R^2. The larger the statistic, the larger the forecasting accuracy improvement of model M_j versus model M_i. Panel C follows Campbell and Thompson (2008) and measures the economic gains reaped by an expected-utility maximizer (details are in section 5.6). Economic gains are in the form of average ex-post realized utility gain of switching from model M_i to model M_j ($M_i vs M_j$), as well as average portfolio returns, and Sharpe ratio obtained using either model. Panel D reports end-of period wealth of an agent who is endowed with \$100 in the month of first out of sample prediction, and rebalances her portfolio once every three or 12 months. With the exception of the Sharpe ratio, results in Panel C are expressed in %. All results in Panel C are annualized.

Panel A: test of equal prediction accuracy

Horizon l		D/P			B/M			E/P	
(months)	M0vsM1	M0vsM2	M1vM2	M0vsM1	M0vsM2	M1vM2	M0vsM1	M0vsM2	M1vM2
3	0.075	0.554	0.419	0.113	1.129	1.018	0.318	1.146	0.9
	[0.291]	[0.845]	[0.78]	[0.637]	[2.029]	[2.094]	[1.118]	[2.283]	[1.929]
12	3.7	49.551	48.92	3.652	53.477	56.243	6.619	55.453	57.94
	[0.846]	[1.843]	[1.706]	[0.978]	[2.027]	[1.904]	[1.278]	[2.027]	[1.828]

Panel B: out of sample R^2

Horizon l		D/P			B/M			CAEP	
(months)	M0vsM1	M0vsM2	M1vM2	M0vsM1	M0vsM2	M1vM2	M0vsM1	M0vsM2	M1vM2
3	-0.20711	-2.73671	-2.52438	0.321473	1.746358	1.42948	1.309304	5.074876	3.815528
12	1.247378	21.52537	20.53413	-0.86599	36.20032	36.74808	1.876371	28.92754	27.56846

Table 7
Out of sample tests(Continued)

Panel C: realized economic gains

Horizon (months)	Predictor	Realized economic gains			Realized mean returns			Sharpe ratio		
		M0vsM1	M0vsM2	M1vsM2	M0	M1	M2	M0	M1	M2
3	D/P	0.595	3.983	3.388	6.444	7.673	10.682	0.211	0.258	0.414
	B/M	-0.38	2.109	2.489	6.444	8.155	8.271	0.211	0.255	0.31
	E/P	1.107	4.548	3.44	6.444	10.041	10.798	0.211	0.327	0.434
12	D/P	0.01	7.313	7.303	5.051	6.19	11.789	0.127	0.164	0.433
	B/M	1.636	10.925	9.289	5.051	9.007	14.627	0.127	0.26	0.591
	E/P	1.661	8.915	7.254	5.051	9.207	13.126	0.127	0.265	0.498

Panel D: End-of-period wealth

Horizon (months)	Predictor	M0	M1	M2
3	D/P	200	267	402
	B/M	200	215	229
	E/P	200	336	372
12	D/P	150	172	361
	B/M	150	257	662
	E/P	150	237	437

Appendix

Table A1
Extrapolation - Conditional stock return predictability, fixed window

Using GMM we estimate the following monthly time-series regression of l-months ahead aggregate excess returns:

$$R^e_{t_0,t_0+l} = a_0 + a_1 DOX_{t_0} + D/P_{t_0}[b_0 + b_1 DOX_{t_0}] + \epsilon^R_{t_0,t_0+l}$$

where $R^e_{t_0,t_0+l}$ is the l-months ahead excess return of a value weighted portfolio of US equities from CRSP, the risk-free rate is from Ken French's website, D/P is the aggregate dividend-price ratio, DOX is the degree of extrapolation extracted from II, AA, or their principal component PC. Panel A reports the results, and includes the univariate predictability regression as a baseline specification. The sample period is 1990:06–2013:12. Panel B and C replace D/P with B/M and E/P, respectively. Coefficients and t-statistics are based on Newey-West standard errors with a lag length of l months.

Panel A: D/P

Horizon (months)	Variable	Baseline	II	AA	PC
3	a_0	-0.024	0.109	0.097	0.134
		[-1.02]	[1.73]	[2.16]	[2.43]
	a_1		-0.325	-0.185	-0.3
			[-2.91]	[-2.60]	[-3.20]
	b_0	2.085	-4.028	-2.593	-4.237
		[1.833]	[-1.51]	[-1.30]	[-1.78]
	b_1		16.485	6.969	12.786
			[3.03]	[1.98]	[2.71]
	$Adj.R^2$ (%)	2.40	8.50	10.50	11.20
12	a_0	-0.116	0.301	0.496	0.554
		[-1.307]	[2.05]	[4.41]	[5.56]
	a_1		-0.894	-0.926	-1.188
			[-3.38]	[-4.50]	[-6.89]
	b_0	9.643	-7.346	-15.787	-15.19
		[2.603]	[-1.34]	[-2.98]	[-3.27]
	b_1		39.066	37.955	45.494
			[2.93]	[3.77]	[4.33]
	$Adj.R^2$ (%)	13.50	21.70	43.80	49.90

Table A1
Extrapolation - Conditional stock return predictability, fixed window (Continued)

Panel B: B/M

Horizon (months)	Variable	Baseline	II	AA	PC
3	a_0	-0.018 [-0.79]	0.094 [1.65]	0.152 [3.00]	0.132 [2.55]
	a_1		-0.245 [-2.40]	-0.249 [-3.50]	-0.275 [-3.50]
	b_0	0.129 [1.795]	-0.246 [-1.20]	-0.37 [-2.25]	-0.317 [-1.76]
	b_1		0.862 [2.11]	0.725 [2.95]	0.84 [2.88]
	$Adj.R^2(\%)$	1.40%	6.00%	9.40%	9.70%
12	a_0	-0.101 [-1.001]	0.328 [2.37]	0.613 [4.82]	0.552 [4.76]
	a_1		-0.909 [-4.12]	-1.051 [-5.45]	-1.168 [-5.68]
	b_0	0.649 [2.23]	-0.657 [-1.58]	-1.516 [-3.85]	-1.171 [-2.90]
	b_1		2.831 [3.51]	3.164 [4.83]	3.289 [4.24]
	$Adj.R^2(\%)$	8.90%	25.00%	37.10%	48.60%

Panel C: E/P

Horizon (months)	Variable	Baseline	II	AA	PC
3	a_0	-0.047 [-1.618]	0.123 [1.50]	0.13 [1.91]	0.167 [2.22]
	a_1		-0.36 [-2.49]	-0.269 [-2.74]	-0.381 [-3.22]
	b_0	1.585 [2.389]	-2.408 [-1.30]	-2.119 [-1.34]	-2.992 [-1.78]
	b_1		8.892 [2.47]	5.589 [2.35]	8.41 [2.96]
	$Adj.R^2$	0.04	0.091	0.11	0.12
12	a_0	-0.185 [-1.655]	0.359 [1.81]	0.711 [4.77]	0.739 [5.65]
	a_1		-1.061 [-3.33]	-1.359 [-5.58]	-1.568 [-6.25]
	b_0	6.366 [2.825]	-5.195 [-1.27]	-12.969 [-3.89]	-12.167 [-3.91]
	b_1		23.178 [2.94]	29.386 [5.02]	31.918 [4.85]
	$Adj.R^2$	0.141	0.246	0.431	0.513

Table A2
Price-scaled predictors: conditional mean-reversion, fixed window

This table reports GMM estimation results for the following conditional autoregressive model:

$$Predictor_{t+12} = a_0 + a_1 * DOX_t + Predictor_t[b_0 + b_1 DOX_t] + \epsilon_t^P$$

The *predictor* variable is one of the following aggregate price-scaled variables: dividend-price (D/P) ratio, the book-to-market (B/M) ratio, and the cyclically adjusted earnings-to-price (E/P). The DOX state variable is extracted from the principal component of the II and AA survey (PC). Newey-West t-statistics with six lags are reported in brackets. P-values for the one-sided null hypothesis $H_0 : b_1 >= 0$ are reported in parenthesis. The sample period is 1990:06–2012:12.

Survey	Horizon (months)		a_0	b_0	a_1	b_1	$Adj.R^2$
		D/P	-0.003	1.003	0.015	-0.525	67%
			[-1.326]	[10.235]	[2.635]	[-1.541]	
PC	12	B/M	0.004	0.906	0.159	-0.466	56%
			[0.084]	[7.272]	[1.665]	[-1.562]	
		E/P	-0.007	1.04	0.033	-0.564	59%
			[-1.201]	[7.771]	[3.401]	[-2.284]	

Table A3
Out of Sample tests, fixed-window

The table presents results of out-of-sample test for the following forecasting models:

$$M_0 : R^e_{t_0,t_0+l} = \mu + \epsilon^{M_0}_{t_0,t_0+l}$$
$$M_1 : R^e_{t_0,t_0+l} = a_0 + b_1 Predictor_{t0} + \epsilon^{M_1}_{t0,t_0+l}$$
$$M_2 : R^e_{t_0,t_0+l} = (a_0 + a_1 DOX_{t0}) + Predictor_{t0}(b_1 + b_2 DOX_{t0}) + \epsilon^{M_2}_{t0,t_0+l}$$

The dependent variable $R^e_{t_0,t_0+l}$ is the l-months ahead cumulative excess return. The *Predictor* variable is one of the following: the dividend-price ratio (D/P), the book-to-market ratio (B/M), or the cyclically adjusted earnings-to-price ratio (E/P). The DOX is extracted from the principal component of the AA and II surveys. Starting in 1995:06, every month m we estimate each model using all observations available between the date of the first DOX estimate (1990:06) and m. We use the parameter estimates available in month m and the value of the right-hand variables in month *(m+l)*, to predict the l-months cumulative return over period *(m+l,m+2l)*. We then collect the ex-post forecast errors for each model. Panel A reports Clark and West (2007) one-sided test statistic for the null hypothesis of equal forecasting accuracy of M_i and M_j against the alternative of forecasting improvement of model M_j (details on can be found in section 5.6). Standard errors are robust to heteroskedasticity and serial correlation with l lags. Panel B presents Campbell and Thompson (2008) measure of out-of-sample R^2. The larger the statistic, the larger the forecasting accuracy improvement of model M_j versus model M_i. Panel C follows Campbell and Thompson (2008) and measures the economic gains reaped by an expected-utility maximizer. (Details are in section 5.6). Economic gains are in the form of average ex-post realized utility gain of switching from model M_i to model M_j ($M_i vs M_j$), as well as average portfolio returns, and Sharpe ratio obtained using either model. Panel C also reports end-of period wealth of an agent who is endowed with $100 in the month of first out of sample prediction, and rebalances her portfolio once every three or 12 months. With the exception of the Sharpe ratio and the end-of-period wealth, results in Panel C are expressed in %. With the exception of the end-of-period wealth, all results in Panel C are annualized.

Panel A: test of equal prediction accuracy

Survey	Horizon (months)	D/P M0vsM1	D/P M0vsM2	D/P M1vM2	B/M M0vsM1	B/M M0vsM2	B/M M1vM2	E/P M0vsM1	E/P M0vsM2	E/P M1vM2
PC	3	0.05	0.754	0.631	0.084	0.906	0.719	0.247	0.908	0.631
		[0.3]	[1.877]	[2.012]	[0.802]	[2.577]	[2.372]	[1.279]	[2.614]	[1.966]
		(0.38)	(0.031)	(0.022)	(0.211)	(0.005)	(0.01)	(0.100)	(0.001)	(0.025)
	12	1.375	23.53	21.642	1.94	21.55	19.475	3.559	26.999	25.523
		[0.464]	[1.974]	[1.898]	[0.808]	[2.000]	[1.773]	[1.01]	[2.266]	[1.904]
		(0.321)	(0.025)	(0.03)	(0.211)	(0.023)	(0.039)	(0.160)	(0.012)	(0.029)

Panel B: out of sample R^2

Survey	Horizon (months)	D/P M0vsM1	D/P M0vsM2	D/P M1vM2	B/M M0vsM1	B/M M0vsM2	B/M M1vM2	E/P M0vsM1	E/P M0vsM2	E/P M1vM2
PC	3	-0.017	2.857	2.874	0.915	5.346	4.472	1.906	6.358	4.539
	12	-1.804	23.209	24.57	0.804	26.852	26.259	0.831	37.335	36.81

Table A3

Out of sample tests, fixed window(Continued)

Panel C: realized economic gains

Survey	Horizon	Predictor	Realized economic gains			Realized mean returns			Sharpe ratio			End of Period Wealth		
	(months)		M0vsM1	M0vsM2	M1vsM2	M0	M1	M2	M0	M1	M2	M0	M1	M2
PC	3	D/P	-0.504	3.555	4.059	9.902	9.342	13.519	0.363	0.337	0.538	428	419	882
		B/M	0.012	3.599	3.588	9.902	10.866	14.054	0.363	0.382	0.543	428	437	872
		E/P	1.001	5.774	4.774	9.902	12.239	15.695	0.363	0.432	0.646	428	621	1584
	12	D/P	-0.149	8.785	8.934	10.031	9.343	15.117	0.295	0.276	0.624	347	324	674
		B/M	2.125	11.338	9.212	10.031	12.25	17.307	0.295	0.377	0.74	347	529	884
		E/P	1.922	12.048	10.126	10.031	12.346	17.577	0.295	0.375	0.793	347	470	919

Table A4
Conditional stock return predictability: Raw returns, capital gains, log excess returns

We estimate the following monthly predictive regression:

$$R_{t_0,t_0+12} = a_0 + a_1 DOX_{t_0} + Predictor_{t_0}[b_0 + b_1 DOX_{t_0}] + \epsilon^R_{t_0,t_0+12}$$

The *Predictor* variable is one of the following: dividend-price ratio (D/P), book-to-market ratio (B/M), or the cyclically adjusted earnings-to-price ratio (E/P). The DOX is extracted from the principal component (PC) of the II and AA surveys, via recursive estimation. (Details are in the paper). R_{t_0,t_0+12} is one of the following: the 12-month raw return on the aggregate value-weighted portfolio of US equities from CRSP, the capital gain component of the return on the same portfolio, the log excess-return on the CRSP value-weighted portfolio of US stocks. When predicting log-quantities, the predictor variable is in logs as well. T-statistics are based on Newey-West standard errors with a lag length of 12 months. The sample period is 1992:06–2013:12.

Horizon	Variable	D/P		B/M		E/P	
(months)							
	a_0	-0.15	0.73	-0.09	0.86	-0.16	0.99
		[-1.43]	[4.95]	[-0.76]	[5.22]	[-1.27]	[4.57]
	a_1		-1.60		-1.76		-2.08
Raw returns			[-6.28]		[-5.24]		[-5.29]
	b_0	13.29	-21.90	0.76	-2.12	6.73	-17.40
		[2.73]	[-2.90]	[2.02]	[-3.68]	[2.53]	[-3.18]
	b_1		64.64		5.27		43.57
			[4.40]		[5.24]		[4.35]
	$Adj.R^2$	14.9%	42.0%	8.4%	46.6%	11.4%	44.2%
		D/P		B/M		E/P	
	a_0	-0.15	0.73	-0.09	0.85	-0.16	0.99
		[-1.45]	[4.92]	[-0.81]	[5.22]	[-1.30]	[4.60]
Capital gains	a_1		-1.59		-1.74		-2.08
			[-6.28]		[-5.28]		[-5.32]
	b_0	12.22	-22.70	0.69	-2.18	6.20	-17.91
		[2.54]	[-3.05]	[1.88]	[-3.84]	[2.30]	[-3.31]
	b_1		64.32		5.27		43.64
			[4.35]		[4.63]		[4.40]
	$Adj.R^2$	13.2%	40.9%	7.4%	45.6%	10.1%	43.2%
		D/P		B/M		E/P	
	a_0	1.17	-1.44	0.37	-0.277	1.04	-1.54
		[3.14]	[-2.79]	[3.9]	[-1.35]	[3.42]	[-2.50]
Logs	a_1		4.82		1.08		4.65
			[4.02]		[2.68]		[3.75]
	b_0	0.28	-0.42	0.23	-0.36	0.31	-0.54
		[2.96]	[-3.29]	[2.93]	[-2.50]	[3.08]	[-2.88]
	b_1		1.28		1.01		1.52
			[4.51]		[3.53]		[4.03]
	$Adj.R^2$	16.1%	39.7%	12.6%	41.3%	14.9%	42.1%

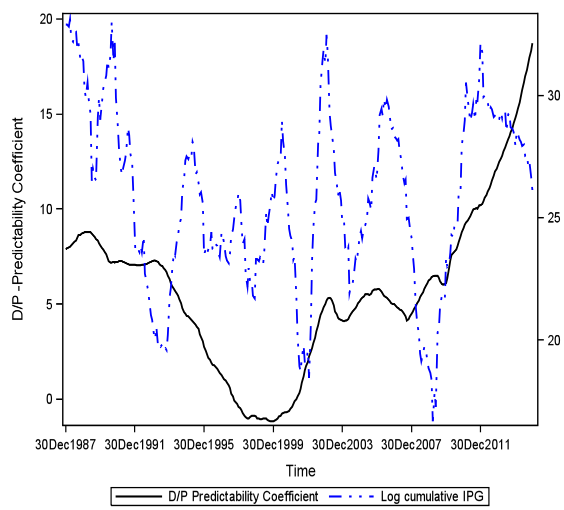
Table A5
Conditional stock return predictability: competing state variables

We extend our specification in Equation 6 to include a set of k conditioning variables in predictive regressions of year-ahead equity premium:

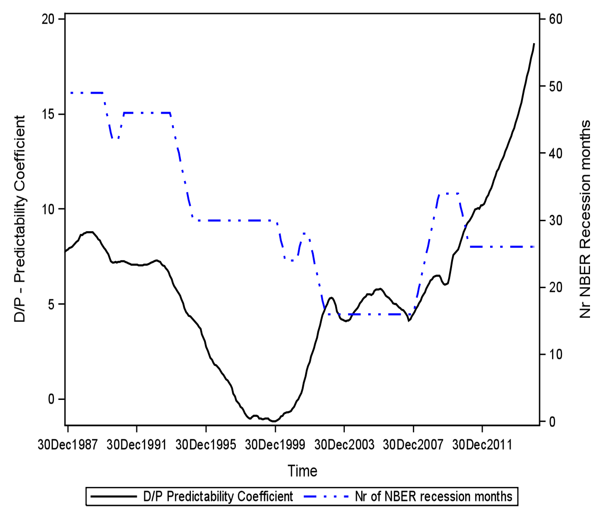
$$R^e{}_{t,t+12} = (A'Z_t) + D/P_t(B'Z_t) + \epsilon^R_{t,t+12}$$

A and B are two (k+1)×1 column vectors of coefficients, whose first row corresponds to the unconditional coefficient a_0 and b_0 in Equation 6, and Z_t is a (k+1)×1 column vector of potential state variables in the predictive regression, which includes the constant 1 in its top row, and stacks all the k state-variables, including the DOX from the PC time-series, in the remaining rows. The competing state variables we consider are: quarterly returns (Qret), the Baker and Wurgler's (2006) measure of investor sentiment (BW), growth in industrial production (IPG), and the NBER recession dummy (NBER_D). Specifications (1) to (4) set k=1 and replace the DOX with one of the competing state variables in the conditional predictability regressions. Specification (5) to (7) set k=2, as they horse race the DOX measure with one competing source of conditional predictability. Specification (8) performs a kitchen-sink regression in which all the competing state variables are included in the model. The regressions that include the BW measure of sentiment are run over the period 1992:06–2010:12. All other regressions are run in the period 1992:06–2013:12. T-statistics are based on Newey-West (1986) with 12 lags.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Int	-0.21	-0.136	-0.212	-0.069	0.698	0.706	0.698	0.92
	[-2.26]	[-1.15]	[-2.28]	[-0.94]	[4.109]	[4.92]	[4.217]	[5.64]
DOX					-1.718	-1.818	-1.676	-2.28
					[-5.291]	[-6.299]	[-5.793]	[-6.87]
IPG	0.194				-0.002			0.014
	[2.68]				[-0.015]			[0.24]
NBER_D		-0.58				-0.235		-0.113
		[-2.14]				[-0.979]		[-0.46]
Qret			1.246				-0.216	-0.101
			[2.83]				[-0.396]	[-0.24]
BW				-0.175				0.28
				[-0.65]				[1.49]
D/P	14.19	12.12	14.34	7.85	-24.754	-24.916	-23.794	-33.73
	[3.25]	[2.2]	[3.3]	[1.82]	[-2.911]	[-3.442]	[-3.009]	[-4.19]
DOX*D/P					77.081	84.764	73.349	103.620
					[4.104]	[5.029]	[4.504]	[5.69]
IPG*D/P	-6.72				2.012			-0.42
	[-2.49]				[0.454]			[-0.16]
NBER_D*D/P		17.490				0.506		-6.92
		[1.59]				[0.052]		[-0.57]
Qret*D/P			-42.72				17.355	-3.38
			[-2.64]				[0.834]	[-0.15]
BW*D/P				3.13				-16.820
				[0.16]				[-1.29]
Adj. R^2	21.20%	32.72%	19.80%	28.30%	41.40%	50.27%	39.63%	54.11%



Panel A: Cumulative IP Growth



Panel B: Number of recession months from NBER

Figure A1
Parameter instability in the predictability relation: competing state variables
In the sample period 1987:12–2013:12, we run monthly univariate predictive regressions of one-year-ahead excess returns on current D/P ratio over a rolling window of 20 years. At the same time, we construct a 20-year log cumulative industrial production growth time-series (Panel A), and a 20-year moving-sum of the number of recessionary months from the NBER (Panel B). The solid line reports the recursively estimated univariate coefficient of predictability, and the dashed line reports the recursively estimated explanatory variable.

Table A6
Parameter instability in the predictability relation: competing state variables

In the period 1987:12–2013:12, we obtain the recursively-estimated coefficient of predictability $\widehat{\beta_{RW\,m}}$ by fitting every month m the following monthly predictive regression of year-ahead excess returns over a rolling window of 20 years:

$$R^e{}_{t,t+12} = a_0 + \beta_{RW\,m} D/P_t + \epsilon^R_{t,t+12} \qquad t \in [m - 20 \times 12 + 1, m]$$

where R^e stands for aggregate excess return on the value-weighted portfolio of CRSP US equities and D/P is the aggregate value weighted dividend-price ratio. At the same time, we estimate a 20-year moving average DOX ($\overline{DOX_{RW\,m}}$) extracted from the extended principal component PC_{ext}, a 20-year moving sum of NBER recessionary months ($\overline{NBER\_D_{RW\,m}}$), and a 20-year cumulative growth in industrial production ($\overline{CUM\_IPG_{RW\,m}}$). We then run the following regressions:

$$\widehat{\beta_{RW\,m}} = a + b(\overline{NBER\_D_{RW\,m}}) + \epsilon_m \qquad (1)$$

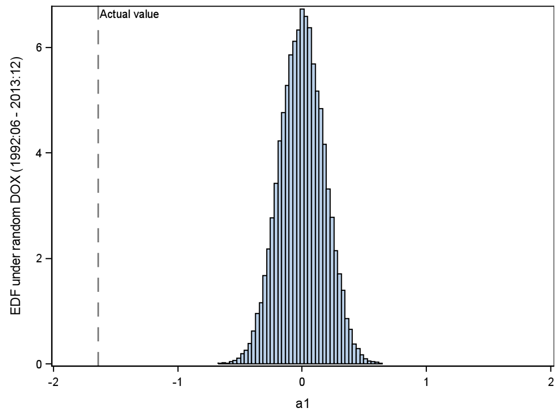
$$\widehat{\beta_{RW\,m}} = a + b(\overline{CUM\_IPG_{RW\,m}}) + \epsilon_m \qquad (2)$$

$$\widehat{\beta_{RW\,m}} = a + b_1(\overline{NBER\_D_{RW\,m}}) + b_2(\overline{CUM\_IPG_{RW\,m}}) + b_3\overline{DOX_{RW\,m}} + \epsilon_m \qquad (3)$$

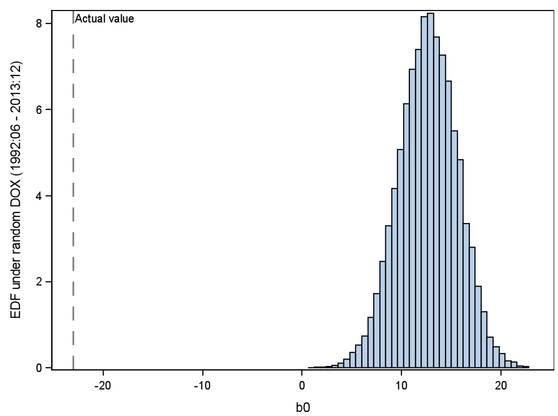
T-statistics are based on Newey-West (1986) with 12 lags.

	(1)	(2)	(3)
Int	4.345	-6.266	-29.141
	[2.80]	[-1.56]	[-8.75]
$NBER\_D_{RW\,m}$	0.140		0.293
	[1.48]		[3.13]
$CUM\_IPG_{RW\,m}$		0.464	0.161
		[3.02]	[1.93]
$DOX_{RW\,m}$			68.426
			[8.4]
Adj. R^2	1.30%	15.80%	78.60%

Panel A: a_1



Panel B: b_0



Panel C: b_1

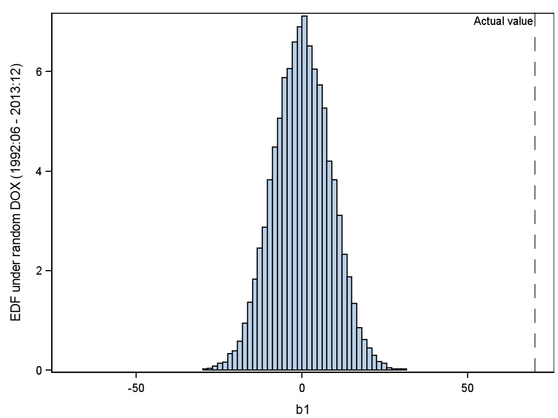


Figure A2
Conditional stock return predictability: falsification test
Using Monte Carlo simulations, we generate 50000 fictitious DOX sequences, whose mean and variance match the mean and the variance of the DOX extracted from the principal component (PC) of the II and AA surveys. We then fit our monthly conditioning predictive model of one-year ahead excess returns

$$R^e{}_{t,t+12} = (a_0 + a_1 DOX_t) + D/P_t(b_0 + b_1 DOX_t) + \epsilon^R_{t,t+12}$$

using the artificially created DOX and draw an empirical distribution of the regressions coefficients. Finally, we place our actual coefficient estimates {a1, b0, b1} presented in Table 5 on the obtained empirical distribution.

Table A7
Small sample: bias correction

We fit the following annual regressions using OLS under the null of no conditional stock return predictability:

$$H_0{}^1: \quad \begin{cases} R^e{}_{t,t+12} & = (a_0 + a_1 DOX_t) + b_0 D/P_t + \epsilon^r_{t,t+12} \\ Predictor_{t+12} & = (\alpha_0 + \alpha_1 DOX_t) + Predictor_t(c_0 + c_1 DOX_t) + \epsilon^P_{t,t+12} \end{cases}$$

where we treat the DOX as non-stochastic. To avoid the complications that may arise due to overlapping observations, we run annual regressions. At the same time, in order to use all available information, we run 12 separate sets of such annual regressions, one for each possible year-end. The estimated error terms are measured after accounting, via a first round of Monte Carlo simulations, for the Kendall (1954) bias in the estimation of the AR(1) coefficient c_0, and for the Stambaugh (1986) bias in the estimation of the coefficient of predictability b_0. We use the bias-corrected estimates of the coefficient in the null system of equations $H_0{}^1$ to construct a joint empirical distribution of disturbance terms $(\epsilon^r_{t,t+12}, \epsilon^P_{t,t+12})$. Subsequently, we draw with replacement from the joint empirical distribution of the errors to create 10000 artificial pairs $(R^{e*}, Predictor^*)$ consistent with the null of no conditional stock return predictability. Using the artificially created series, we subsequently estimate the return equation implied by the alternative hypothesis:

$$R^{e*}_{t,t+12} = (a_0 + a_1 DOX_t) + Predictor_t{}^*(b_0 + b_1 DOX_t) + \epsilon^R_{t,t+12}$$

which is identical to the one used in our main test in Table 5. We collect the simulated coefficient estimates of interest $b_1{}^*$ from each year-end regression, and aggregate them into a unique empirical distribution of 120000 estimates. Results are presented in Panel A, where we report the overall average of the coefficient estimates ($E[b_1{}^*]$), the actual coefficient estimate (b_1) from Table 5, the ratio of the average simulated coefficient estimate to the actual estimate ($E[b_1{}^*]/b_1$), and the one-sided empirical probability of obtaining, under the null, a coefficient $b_1{}^*$ that is of the same sign and as large as our actual full-sample coefficient estimate b_1.
In Panel B, we report simulation results for a second setting ($H_0{}^2$), in which we acknowledge the joint nature of our hypothesis of conditional stock return predictability, and accordingly modify the initial null hypothesis by imposing the further restriction $c_1 = 0$.

Panel A: $H_0{}^1$

Survey	Predictor	$E[b_1{}^*]$	b_1	$b_1 - E[b_1{}^*]$	$E[b_1{}^*]/b_1$ (%)	One-sided p
PC	D/P	1.506	70.26	68.754	2.10%	0.063
	B/M	-0.001	5.11	5.111	0.00%	0.06
	E/P	-2.565	45.034	47.599	-5.70%	0.029
II	D/P	3.555	61.37	57.815	5.80%	0.129
	B/M	-0.096	4.59	4.686	-2.10%	0.095
	E/P	-2.657	40.08	42.737	-6.60%	0.065
AA	D/P	1.287	69.431	68.144	1.90%	0.047
	B/M	0.023	5.46	5.437	0.40%	0.05
	E/P	-0.68	49.008	49.688	-1.40%	0.036

Panel A: $H_0{}^2$

Survey	Predictor	$E[b_1{}^*]$	b_1	$b_1 - E[b_1{}^*]$	$E[b_1{}^*]/b_1$ (%)	One-sided p
PC	D/P	7.723	70.26	62.537	11.00%	0.092
	B/M	0.129	5.11	4.981	2.50%	0.063
	E/P	1.452	45.034	43.582	3.20%	0.051
II	D/P	6.45	61.37	54.92	10.50%	0.149
	B/M	-0.002	61.37	61.372	0.00%	0
	E/P	0.167	40.08	39.913	0.40%	0.09
AA	D/P	3.974	69.431	65.457	5.70%	0.079
	B/M	0.079	5.46	5.381	1.40%	0.056
	E/P	0.188	49.008	48.82	0.40%	0.041