Extrapolators at the Gate: Market-wide Misvaluation and the Value Premium *

Stefano Cassella
Tilburg University

Zhaojing Chen
Renmin University of China

Huseyin Gulen
Purdue University

Ralitsa Petkova
Case Western Reserve University

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Abstract

We show that the magnitude of the value premium over 1968-2018 is conditional on aggregate market-wide misvaluation. The value premium is 3.42% per month following market-wide undervaluation, 1.70% per month following market-wide overvaluation, and close to being nonexistent following periods in which the aggregate market is neither significantly over- or undervalued. Going from normal valuation states to market-wide overvaluation (undervaluation), the increase in the value premium is due primarily to the poor (good) performance of growth (value) stocks. We show theoretically that these facts can be reconciled in a model in which some investors overextrapolate the past performance of stocks. In our model, extrapolators' demand for value and growth stocks depends not only on the relative performance of these stocks but also on the overall performance of the stock market, which causes investors with extrapolative beliefs to move capital in and out of the equity market. This extrapolative asset-class switching behavior helps explain both the conditionality of the value premium and the drivers of the premium in different market-wide misvaluation states.

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1 Introduction

Ample evidence suggests that valuation ratios predict stock returns. At the aggregate level, existing literature has documented that price-scaled variables (B/M, E/P, CF/P) predict subsequent stock market returns. In the cross section, the value premium, i.e., the fact that stocks with relatively high fundamental-to-price ratios (value stocks) have higher expected returns than stocks with relatively low fundamental-to-price ratios (growth stocks), is one of the most popular empirical regularities.[1]

In this paper, we present striking new evidence on the value premium. We show that the profitability of the value-minus-growth strategy is conditional on market-wide misvaluation. Specifically, the value premium is significantly higher following periods of extreme market-wide valuation, with either the long (value) or the short (growth) leg of the strategy playing a bigger role depending on the nature of market-wide misvaluation. We find that significant market-wide overvaluation states coincide with significant overvaluation of growth stocks, but no extreme misvaluation of value stocks. Similarly, in states of significant market-wide undervaluation, value stocks are significantly undervalued, but growth stocks are not. Accordingly, we find that the increase in the value premium following market-wide overvaluation (undervaluation) is mainly due to the worsening (improving) performance of growth (value) stocks compared to normal market-wide valuation states.[2] Furthermore, following periods of normal market-wide valuations, the value premium is considerably smaller. For example, in the month following normal valuation states the value premium is not significantly different from zero, while it is 3.42% and 1.70% following undervaluation and overvaluation, respectively.[3]

We argue that both time-series predictability by price-scaled variables and these striking new facts about the time variation in the value premium can arise in an economy in which agents overextrapolate the past returns of risky assets. At the aggregate level, recent work in behavioral finance already ties the predictive ability of price-scaled variables and its time-series variation to the presence of extrapolators in the market (e.g., Barberis et al (2015), Cassella and Gulen (2018)).[4] We argue and show that over-extrapolation drives not only the time-series predictability of the aggregate market return, but it also has a direct effect on the magnitude of and the time-series

[1]For predictability at the aggregate level, see Fama and French (1988), Campbell and Shiller (1988), Cochrane (1992, 2008, 2011) for dividend-to-price (D/P), Lewellen (2004) for book-to-market (B/M), and Campbell and Shiller (1988) for earnings-to-price (E/P). Numerous studies have also documented that there is a positive cross-sectional relation between average stock returns and book-to-market, cash-flow-to-price, and earnings-to-price ratios. See, for example, Stattman (1980), Rosenberg, Reid, and Lanstein (1985), Basu (1983), Chan, Hamao, and Lakonishok (1991), Fama and French (1992), among others.

[2]Throughout the paper, "normal market-wide valuation states" or "normal valuation states" refers to states in which the market is neither significantly overvalued nor significantly undervalued.

[3]Furthermore, for value-weighted returns, the entire value premium is driven by periods following market-wide misvaluation states.

[4]The idea that investors have extrapolative beliefs has existed for a long time. Under extrapolative beliefs, people's expectation of the future return of an asset is a weighted average of the past returns of the asset. Initial research on the topic includes Cutler, Poterba, and Summers (1990), Frankel and Froot (1990), De Long et al (1990a), Hong and Stein (1999), and Barberis and Shleifer (2003). More recent studies on the topic include Barberis et al (2015, 2018), Glaeser and Nathanson (2017), Cassella and Gulen (2019), DeFusco, Nathanson, and Zwick (2021), Jin and Sui (2021), and Lou and Polk (2021).

variation in the profitability of the value premium, which is a cross-sectional phenomenon.

To formalize our argument, we set up a stylized model of financial markets with extrapolators that builds on Barberis and Shleifer (2003). The intuition of our model is simple. When stocks, on average, go up in response to positive cash-flow news, extrapolative demand for equities goes up, either because new extrapolators enter the stock market or because existing extrapolators move capital into stocks either from other risky assets such as bonds and real estate, or cash. As extrapolators are drawn into the market, they not only amplify the initial price jump of equities at large (causing overvaluation and eventual poor performance of the market as in Barberis et al (2015) and Cassella and Gulen (2018)), but furthermore, they invest more in stocks with relatively more positive cash-flow shocks and higher returns. This extrapolative demand based on asset allocation is in addition to the extrapolative demand for better-performing stocks emanating from within-equity switchers who direct more capital to recent winners by shorting stocks with poor recent performance. As a result of the additional extrapolative demand for better-performing stocks, such stocks become significantly overvalued. These stocks will have a significantly high price relative to fundamental value and are more likely to be classified as growth stocks at portfolio formation. The subsequent correction of this overvaluation results in the cross-sectional value premium, i.e., the return spread between value and growth stocks.

Similarly, following periods in which stocks, on average, experience negative cash-flow shocks and average returns are low, extrapolators move capital out of stocks and do so by disproportionately selling poor-performing stocks. This is in addition to the shorting behavior of within-equity switchers towards these stocks. As a result, such stocks become significantly undervalued. These stocks will have a significantly low price relative to fundamental value and are more likely to be classified as value stocks at portfolio formation. The cross-sectional value premium is realized when these stocks rebound from being undervalued. The impact of extrapolative capital flows in and out of the stock market on cross-sectional predictability has been overlooked in the previous literature, and our paper fills this gap.

Our model introduces several new predictions on the value premium. First, the model suggests that the value premium is larger following extreme market-wide over- or undervaluation. This is because growth stocks become significantly overvalued leading up to market-wide overvaluation states, whereas value stocks become significantly undervalued leading up to market-wide undervaluation. Second, our model predicts that the cross-sectional value premium should largely stem from the poor performance of growth stocks following periods of significant market-wide overvaluation and the good performance of value stocks following periods of significant market-wide undervaluation. Finally, our model implies that the value premium emanates from investors (over)extrapolating the recent performance of equities both at the aggregate level and in the cross section.

Testing the predictions of our model requires a measure of market-wide misvaluation. We construct such a measure that is implementable in real-time and does not have a look-ahead bias. Since, in our model, the valuation ratio of the market is the equally-weighted average of B/M ratios of all stocks, we use the cross-sectional average of the B/M ratios of all stocks as a measure of market-wide valuation.[5] To measure the degree of market-wide *misvaluation*, we need a benchmark for the fair value of stocks on average. To this end, we use the long-run historical (time-series) distribution of the cross-sectional average of firm-level B/M ratios as the valuation benchmark. This is based on the idea that the long-run average of market-wide B/M ratios represents the mean value to which market-wide B/M ratios revert and the premise that the historical distribution of the market-wide B/M ratio represents a data-driven proxy of the long-run distribution of the market valuation.

Using this approach, we develop a measure of market-wide misvaluation which compares the current cross-sectional average B/M ratio to the historical distribution of the cross-sectional average B/M ratios.[6] The periods in which the market-wide B/M ratio is in the tails of the benchmark distribution signal significant market-wide misvaluation. For example, states in which the cross-sectional average B/M is above (below) the 90^{th} (10^{th}) percentile of its long-run historical distribution represent cases when stocks are significantly undervalued (overvalued) compared to the benchmark distribution. We refer to this measure as RMV, a shorthand for "relative market-wide valuation". It is based on the position of the cross-sectional average B/M ratio relative to the historical benchmark distribution (i.e., the historical long-run mean).[7]

Using RMV, we test the main predictions of our model. We show that, over the period from 1968 to 2018, the profitability of the standard value-minus-growth strategy is conditional on the degree of market-wide misvaluation. For example, we find that following states in which the cross-sectional average B/M is above the 90^{th} percentile of its long-run historical distribution (i.e., when the market is significantly undervalued), the value premium is 3.42% per month with a t-statistic of 4.15 in the subsequent month. Similarly, when the average B/M is below the 10^{th} percentile of its historical distribution (i.e., the market is significantly overvalued), the value premium is a highly significant 1.70% per month. More importantly, we show that in the month following periods in which the aggregate B/M ratio is not in the tails of its historical benchmark distribution, the value premium is small and not statistically significant.[8] We observe similar patterns for a holding period of one year. For example, the value premium is 1.22% and 2.80% per-month following market-wide over- and undervaluation (using 10^{th} and 90^{th} percentiles), respectively. Following periods of no significant market-wide misvaluation, the average value premium drops to 0.60% per

[5]Going forward, when we say market-wide or aggregate B/M ratio we mean the cross-sectional average of firm-level B/M ratios. Also, in the rest of the paper, we present results based on B/M for brevity. We obtain similar results, reported in the Internet Appendix, when we use other price-scaled variables such as earnings-to-price (E/P) or cash-flow-to-price (CF/P).

[6]More specifically, for each month t we use the previous 10 years of the time series of aggregate B/M ratios as the benchmark historical distribution of market-wide valuations. This gives us 120 monthly average B/M ratios for the benchmark B/M distribution measured over $[t-120, t-1]$. The current market-wide B/M ratio is then compared to its historical benchmark to determine whether there is market-wide over- or undervaluation. Since we rely on the idea that market-wide B/M ratios revert to the mean in the long run, any significant deviation of the current market-wide B/M ratio from its historical benchmark would suggest over- or undervaluation. We obtain similar results when we use a 20-year rolling window for the benchmark distribution.

[7]In the Internet Appendix, we present results based on an alternative measure that identifies extreme misvaluation states by comparing the entire recent cross section of B/M ratios to the benchmark panel distribution using a non-parametric Mann-Whitney z-statistic. Results are qualitatively similar when we use this alternative measure.

[8]For example, in 60% (80%) of our sample in which there is no significant market-wide misvaluation, the value premium is -0.01% (0.28%) with t-statistics of -0.03 (1.01) in the month following portfolio formation.

month over the same investment horizon.[9] Overall, these results suggest that the value premium mainly emanates from periods in which the most recent cross-section of B/M ratios has shifted significantly in either direction relative to the benchmark distribution. These results are consistent with the key prediction of our model.

We also find strong support for the second prediction of the model, namely that the larger value premium following extreme market-wide misvaluation is driven by different legs of the value strategy depending on the type of misvaluation in the market. Specifically, we find that in the year following market-wide overvaluation, the value premium is mainly driven by the poor performance of growth stocks. For example, of the 1.22% monthly spread following periods of overvaluation, 0.83% comes from the underperformance of growth stocks relative to the median decile, and 0.39% comes from the overperformance of value stocks relative to the median decile. Similarly, in the year following market-wide undervaluation, the value premium is mainly driven by the good performance of value stocks. For example, of the 2.80% monthly spread following periods of undervaluation, 1.94% comes from the overperformance of value stocks relative to the median decile, and 0.86% comes from the underperformance of growth stocks.[10] A similar asymmetry is evident in Jensen's alphas. Following overvaluation periods, the monthly alpha of growth stocks is -0.79% compared to the alpha of value stocks which is 0.42%. Similarly, following periods of undervaluation, the monthly alpha of value stocks is 3.18% compared to 0.19% for growth stocks. Finally, consistent with our post-portfolio formation return evidence, we document that in periods of market-wide overvaluation, growth stocks become significantly overvalued relative to the historical benchmark of stock-level valuation ratios. Similarly, in periods of market-wide undervaluation, value stocks become significantly undervalued. Thus, the observed asymmetry in the drivers of the value premium following significant market-wide misvaluation is mainly driven by the price corrections of the significantly-misvalued legs of the value strategy.

Next, we provide evidence consistent with the theoretical mechanism of the model. Our main premise is that when stocks on average receive good cash-flow news, the magnitude of such news is disproportionately higher for growth stocks, pushing their returns higher. This, in turn, attracts extrapolators disproportionately more to growth stocks, causing them to be significantly overvalued when the market is classified as overvalued.[11] To this end, we show that, compared to value stocks, growth stocks experience significantly higher cash-flow shocks (as measured by standardized unexpected earnings) during the year leading up to significant market-wide overvaluation and end up being significantly overvalued. Similarly, consistent with our setting, we find that value stocks have significantly more negative cash-flow shocks than growth stocks in the year leading up to market-wide undervaluation.

[9]The existence of a value premium, albeit small, over the year following periods of no significant market-wide misvaluation suggests that cross-sectional demand shifts contribute to the value premium.

[10]In contrast, following periods of normal valuation, value and growth stocks contribute almost equally to the value premium. For example, value (growth) stocks earn 0.21% (0.39%) higher (lower) return than the stocks in the middle B/M decile. This symmetry is consistent with our framework in which within-equity demand shifts explain the value premium in normal valuation periods.

[11]These stocks have a high price relative to fundamentals at portfolio formation, hence a growth classification.

Another premise of our model is that extrapolative capital flows into equities leading up to significant market-wide overvaluation and out of equities leading up to undervaluation. Using data on mutual fund flows from the Investment Company Institute (ICI), we show that there are large capital flows into (outflows from) equities leading up to market-wide overvaluation (undervaluation). This finding is consistent with our conjecture that investors (asset-class switchers) move in and out of the market, leading up to significant market-wide misvaluation.

To assess the extent to which the results mentioned above are driven by return extrapolation, the main behavioral argument in our model, we conduct a battery of tests. We first use a survey-based proxy for investors' extrapolative expectations about future stock market returns. This proxy allows us to identify periods characterized by significantly high or low extrapolative expectations about future market returns. Using this proxy, we show that growth stocks experience large positive returns in periods leading up to market-wide overvaluation, especially when investors' expectations about the future market return are also high. Similarly, value stocks experience large negative returns in periods leading up to market-wide undervaluation when investors' expectations about the future market return are low. Accordingly, the value premium and the associated asymmetry in the drivers of the premium are stronger when extreme misvaluation states are characterized by more extreme extrapolative beliefs. In summary, using extrapolative beliefs from survey data, we show that the significant reversal in performance for growth stocks following market-wide overvaluation and value stocks following market-wide undervaluation is more pronounced when investors have (over)extrapolative expectations.

Next, we present more direct evidence in support of the extrapolation channel using investor return expectations in a cross section of U.S. stocks. In particular, following Da, Huang, and Jin (2021), we use data from an online crowdsourcing platform called Forcerank, which organizes weekly contests where individuals are asked to rank stocks based on their expectations of returns over the following week. The ranking of stocks by the participants in the contests allows us to quantify expectations on the relative performance of value and growth stocks. Consistent with the return extrapolation explanation, we show that investors (over)extrapolate the good performance of growth stocks leading up to market-wide overvaluation, both relative to value stocks and relative to growth stocks leading up to normal valuation periods.

We find similar results when we infer expectations about individual stock returns from revisions in price targets by security analysts. We show that leading up to market-wide misvaluation, price target revisions are positively and significantly related to lagged stock returns. More importantly, consistent with the predictions of our model, this dependence is stronger for growth stocks leading up to market-wide overvaluation and for value stocks leading up to market-wide undervaluation.

We present further evidence on return extrapolation by investigating the dependence of order imbalance for value and growth stocks on past returns leading up to different market-wide valuation states. We find that periods leading up to market-wide overvaluation are associated with strong buying demand for growth stocks that depends significantly on lagged returns. Similarly, leading up to market-wide undervaluation, the selling demand for value stocks is significantly related to the poor past performance of these stocks.

Finally, we test whether two alternative explanations can account for our main findings. First, we examine whether measures of fundamental extrapolation exhibit similar behavior to the measures of return extrapolation.[12] Namely, for value and growth stocks and in periods leading up to market-wide misvaluation, we look at the dependence of analysts' earnings forecast revisions on past earnings growth and the dependence of order imbalance on past growth in firm-level return-on-equity. We show that fundamental extrapolation alone is less likely to capture the documented pattern in the value premium. Second, we test whether the conditional behavior of the value premium is consistent with a risk story, using conditional CAPM tests.[13] We find that the spread in betas between value and growth stocks is too small to generate the size of the value premium that we document. For example, following states of significant market-wide undervaluation, the spread in CAPM betas between value and growth stocks is 0.63. To explain the average monthly value premium that we document following such states, the subsequent realized equity risk premium must be unrealistically large. Following states of significant overvaluation, explaining the value premium with conditional betas is even more challenging, as the beta spread between value and growth stocks is -0.14.

Our paper contributes to the growing literature on the role of (over)extrapolative expectations in time-series and cross-sectional predictability. Prior theoretical work on cross-sectional predictability and extrapolative beliefs (i.e., Barberis and Shleifer (2003)) suggests that the value premium can emanate from within-equity demand shifts driven by differences in relative stock performance. In such a framework, the value-minus-growth anomaly exists every period, and the overvaluation of growth stocks and undervaluation of value stocks contribute equally to the profitability of the value strategy (i.e., the extra demand for growth stocks comes from reduced demand for value stocks, resulting in a symmetric move in value and growth stocks' valuations).

However, time-series data show that the relative contribution of value and growth stock returns to the value premium is highly asymmetric. In Figure 1, we calculate the difference in 12-month average returns between the mid book-to-market decile and growth stocks, and the difference in 12-month average returns between value stocks and the mid book-to-market decile. We plot the log ratio of the two return differentials. If value and growth stocks' return movements after portfolio formation contribute equally to the value premium, we expect this log ratio to be equal to 0. Panel A of Figure 1 shows that there are extended periods of time in which value stocks generate the lion's share of the value premium (plot below 0) and periods in which growth stocks are a more important contributor to the value premium (plot above 0). The asymmetric and

[12] Fundamental extrapolation reflects the tendency of investors to extrapolate past firm fundamentals when forecasting future fundamentals.

[13] Petkova and Zhang (2005) show that the risk of growth stocks is higher than the risk of value stocks in good times. As good times represent periods of decreasing marginal utility and declining risk premia, subsequent market returns are lower, and high-beta stocks (growth stocks) do worse than low-beta stocks (value stocks), thus generating a value premium. Similarly, in bad times, value stocks are high-beta stocks compared to growth stocks. As marginal utility rises during economic downturns and investors command a higher premium to hold risky stocks, bad times are followed by higher returns in the future, particularly so for high-beta stocks (value stocks) than low-beta stocks (growth stocks).

time-varying role of value and growth stocks in the realized value premium is difficult to reconcile with within-equity theories of extrapolation. However, this asymmetry can arise naturally in a richer theoretical framework that not only accounts for irrational demand for value and growth stocks within an equity universe but also accommodates variation in aggregate extrapolative capital flows in and out of the equity market. This is evident in Panel B of Figure 1, which shows that the relative contribution of value and growth stocks to the value strategy is in line with the framework developed in our model (i.e., growth stocks contribute more to the value premium following market-wide overvaluation, as measured by RMV, while value stocks contribute more following market-wide undervaluation). Previous theoretical work does not consider the role played by aggregate extrapolative demand for equities in explaining cross-sectional predictability. We show that variation in aggregate extrapolative demand for equities is important in capturing variation in the value premium.

Our paper also contributes to a growing literature on the timing of cross-sectional portfolio returns (e.g., Cooper, Gutierrez, and Hameed (2004), Ali, Daniel, and Hirshleifer (2017), Lou and Polk (2021)). The majority of previous studies on the timing of the value premium have examined variation in the profitability of value investing in relation to the spread in valuation between value and growth portfolios, i.e., the value spread (Asness et al (2000), Cohen, Polk, and Vuolteenaho (2003), Asness et al (2021), Baba Yara, Boons, and Tamoni (2021)). We differ from these studies both empirically and conceptually. From an empirical standpoint, we show that even after controlling for the value spread used in Cohen, Polk, and Vuolteenaho (2003), as well as other variables, the degree of market-wide misvaluation continues to display significant predictive power for the value strategy. Conceptually, we differ from previous papers since we show that both asset-class and within-equity switching behavior due to extrapolative beliefs help explain the value premium. In addition, our theory implies that there is an asymmetry in the sources of the value premium in good and bad times: the value premium largely emanates from either significant overvaluation of growth stocks following market-wide overvaluation or significant undervaluation of value stocks following market-wide undervaluation.

Finally, we contribute to the debate on whether the value premium is due to risk or mispricing. Ever since the value premium was included as part of an asset-pricing model by Fama and French (1993), abundant research debating the sources of the premium has emerged. While some argue that the difference in returns between value and growth stocks reflects compensation for risk,[14] others argue that the value effect is a result of mispricing.[15] We document that the value premium is

[14]For example, Fama and French (1993) link the value premium to distress risk, Lettau and Wachter (2007) offer an explanation based on cash-flow duration, Campbell, Polk, and Vuolteenaho (2010) show that growth stocks have high betas with the market discount-rate shocks, while value stocks have high betas with the market cash-flow shocks, Hansen, Heaton, and Li (2008) explain the value premium based on the covariance of cash-flow growth with consumption in the long run, Koijen, Lustig, and Van Nieuwerburgh (2017) argue that the value premium reflects compensation for macroeconomic risk, Zhang (2005) offers an explanation based on costly reversibility and a countercyclical price of risk.

[15]According to mispricing-based explanations for the value effect, the book-to-market ratio reflects systematically optimistic and pessimistic performance expectations for growth and value stocks, respectively. Under this view, the value premium captures price corrections arising from the reversal of these expectation errors. See, for example,

only evident following extreme valuation periods. This cannot be easily reconciled with traditional risk-based stories. We argue and provide further evidence that the value premium is more likely related to errors in investor expectations.

2 Theoretical Framework

In this section, we present a stylized model of financial markets with return extrapolators. The goal of the model is to investigate the joint dynamics of market prices and individual asset prices in the cross section when extrapolation leads to both overall demand for equities and within-equity demand for value and growth stocks.

To develop our model, we follow Barberis and Shleifer (2003) who examine an economy populated by extrapolators who form expectations based on past returns. We consider an economy with T periods, 2 asset classes, $2n$ risky assets in fixed supply, and a risk-free asset with zero net return in perfectly elastic supply. Each risky asset i is a claim to a liquidating dividend $D_{i,T}$ to be paid at the final date T. The final dividend is:

$$D_{i,T} = D_{i,0} + \epsilon_{i,1} + ... + \epsilon_{i,T}, \tag{1}$$

where $D_{i,0}$ and $\epsilon_{i,t}$ are announced at time 0 and time t, respectively, and where

$$\epsilon_t = (\epsilon_{1,t}, ..., \epsilon_{2n,t})' \sim N(0, \Sigma_D), \text{ i.i.d. over time.} \tag{2}$$

There are three types of investors in the model: within-equity switchers (denoted as SS in the subsequent equations), asset-class switchers (AS), and fundamental traders. Within-equity switchers categorize risky assets into two groups, referred to as X and Y. Each risky asset group consists of n individual assets. We denote the price of stocks in each group, as well as the price of the market portfolio (an equal-weighted average of all risky assets) as $P_{X,t}$, $P_{Y,t}$, and $P_{M,t}$, respectively, where

$$P_{X,t} = \frac{1}{n}\sum_{i\in X} P_{i,t}, \quad P_{Y,t} = \frac{1}{n}\sum_{j\in Y} P_{j,t}, \quad P_{M,t} = \frac{1}{2n}\sum_{l\in X or Y} P_{l,t}. \tag{3}$$

The returns of stocks in group X, group Y, and the market between time $t-1$ and t are

$$\Delta P_{X,t} = P_{X,t} - P_{X,t-1}, \quad \Delta P_{Y,t} = P_{Y,t} - P_{Y,t-1}, \quad \Delta P_{M,t} = P_{M,t} - P_{M,t-1}. \tag{4}$$

We assume that the covariance matrix of cash-flow shocks has the same structure as in the model of Barberis and Shleifer (2003), so that

$$\Sigma_{ij}^D = \begin{cases} 1 & i = j, \\ \psi_M^2 + \psi_S^2 & i,j \text{ in the same stock group, } i \neq j, \\ \psi_M^2 & i,j \text{ in different stock groups.} \end{cases} \tag{5}$$

Within-equity switchers allocate between groups X and Y based on the relative past performance

Lakonishok, Shleifer, and Vishny (1994).

of stocks in these groups.[16] Specifically, within-equity extrapolators' demand for stocks in groups X and Y is summarized by the following equations:

$$N_{i,t}^{SS} = \frac{1}{n}\sum_{k=1}^{t-1}\theta^{k-1}(\Delta P_{X,t-k} - \Delta P_{Y,t-k}) = \frac{N_{X,t}^{SS}}{n}, \quad i \in X \tag{6}$$

$$N_{j,t}^{SS} = \frac{1}{n}\sum_{k=1}^{t-1}\theta^{k-1}(\Delta P_{Y,t-k} - \Delta P_{X,t-k}) = \frac{N_{Y,t}^{SS}}{n}, \quad j \in Y \tag{7}$$

where θ is a constant with $0 < \theta < 1$, which measures the weight within-equity switchers assign to recent versus distant stock performance when comparing X and Y. Within-equity switchers demand the same number of shares for groups X and Y but with opposite signs.

Our model differs from Barberis and Shleifer (2003) by introducing an additional type of extrapolators, referred to as *asset-class switchers*. These investors allocate capital between equities (i.e., the market) and cash based on past market returns. We assume that asset-class switchers have CARA preferences, and their demand for risky assets is derived by solving

$$\underset{N_{M,t}^{AS}}{\text{Max}} \ E_t^{AS}[-e^{-\gamma(W_t^{AS} + N_{M,t}^{AS}(\tilde{P}_{M,t+1} - P_{M,t}))}], \tag{8}$$

where $P_{M,t}$ is defined in Eq.(3). If conditional market price changes follow a Normal distribution, the optimal holding in risky assets for asset-class switchers, $N_{M,t}^{AS}$, is given by

$$N_{M,t}^{AS} = \frac{1}{\gamma} \times Var_t^{AS}(\Delta P_{M,t+1})^{-1} E_t^{AS}[\Delta P_{M,t+1}]. \tag{9}$$

We assume that asset-class switchers put the same weight of θ on more recent past returns as within-equity switchers. More specifically,

$$E_t^{AS}(\Delta P_{M,t+1}) = \theta E_{t-1}^{AS}(\Delta P_{M,t}) + (1-\theta)\Delta P_{M,t-1}, \tag{10}$$

which implies

$$E_t^{AS}(\Delta P_{M,t+1}) = (1-\theta)\sum_{k=1}^{t-1}\theta^{k-1}\Delta P_{M,t-k}. \tag{11}$$

Combining Eq.(9) and Eq.(11), and dropping the non-stochastic terms for simplicity, we can write asset-class switchers' demand for risky assets as an increasing function of the past performance of the market:

$$N_{M,t}^{AS} = \sum_{k=1}^{t-1}\theta^{k-1}\Delta P_{M,t-k}. \tag{12}$$

where $\Delta P_{M,t-k}$ is the market return k periods ago.

An important feature of asset-class switchers that we introduce in the model is that when these investors increase (decrease) their exposure to risky assets, they do so unevenly across stocks. Namely, when asset-class switchers increase their demand for equities, this demand is directed

[16] These investors' demand for stocks in the cross section is similar in spirit to the style-switchers' demand in Barberis and Shleifer (2003). In our case, groups X and Y are stocks that experienced positive or negative cash-flow shocks in the recent past.

mainly to the better-performing stocks in the market. Without loss of generality, we assume that stocks in group X fulfill this criterion. Conversely, when asset-class switchers reduce their demand for equities, they divest more aggressively from stocks that have done especially poorly recently. We assume that stocks in group Y fulfill this criterion. Overall, asset-class switchers' demand for stocks in X and Y is state-contingent and can be summarized as follows:

$$N_{i,t}^{AS} = \begin{cases} 2N_{M,t}^{AS} & \text{if } N_{M,t}^{AS} > 0 \\ 0 & \text{if } N_{M,t}^{AS} \leq 0. \end{cases}, \quad i \in X \qquad (13) \qquad N_{j,t}^{AS} = \begin{cases} 0 & \text{if } N_{M,t}^{AS} > 0 \\ 2N_{M,t}^{AS} & \text{if } N_{M,t}^{AS} \geq 0. \end{cases} \quad j \in Y \qquad (14)$$

Combining within-equity and asset-class switchers' demand, total share demand from extrapolators, N_t^E, is given by:

$$N_t^E = N_t^{SS} + N_t^{AS}, \tag{15}$$

where $N_t^{SS} = (N_{1,t}^{SS}, ..., N_{2n,t}^{SS})$ and $N_t^{AS} = (N_{1,t}^{AS}, ..., N_{2n,t}^{AS})$. Thus, the additional demand for risky assets from asset-class switchers has an amplifying effect on the demand coming from within-equity switchers.

The third investor type in our model features fundamental traders, who act as arbitrageurs and try to prevent the price of risky assets from deviating too far from fundamentals. In contrast to within-equity and asset-class switchers, fundamental traders do not categorize risky assets into groups, and their expectations about risky asset returns do not depend on past performance. Fundamental traders solve

$$\underset{N_t^F}{\text{Max}} \;\; E_t^F[-e^{-\gamma(W_t^F + N_t^{F'}(\tilde{P}_{t+1} - P_t))}], \tag{16}$$

where

$$N_t^F = (N_{1,t}^F, ..., N_{2n,t}^F)', \;\; P_t = (P_{1,t}, ..., P_{2n,t})'. \tag{17}$$

If conditional price changes have a Normal distribution, then the optimal holdings of fundamental traders, N_t^F, are given by

$$N_t^F = \frac{1}{\gamma} \times Var_t^F(\Delta P_{t+1})^{-1} E_t^F[\Delta P_{t+1}]. \tag{18}$$

As in Barberis and Shleifer (2003), fundamental traders in our model serve as market makers. They treat the demand from extrapolators as a supply shock. Suppose that the total supply of the $2n$ risky assets is given by $\boldsymbol{Q}$. Then, rearranging Eq.(18) results in

$$P_t = E_t^F(P_{t+1}) - \gamma Var_t^F(\Delta P_{t+1})(Q - N_t^E), \tag{19}$$

where N_t^E is defined in Eq.(15). The price forecast of fundamental traders is based on their conditional expectation of the final dividend, D_T. At time $T-1$, we have

$$E_{T-1}^F(P_T) = E_{T-1}^F(D_T) = D_{T-1}. \tag{20}$$

Rolling Eq.(19) forward iteratively, and further assuming that $Var_t^F(\Delta P_{t+1}) = V$ and $E_t^F(N_{t+k}^E) =$

$\bar{N}^E$, results in

$$P_t = D_t - \gamma V(Q - N_t^E) - (T - t - 1)\gamma V(Q - \bar{N}^E). \tag{21}$$

Dropping the non-stochastic terms, we obtain

$$P_t = D_t + \gamma V(N_t^{SS} + N_t^{AS}), \tag{22}$$

where P_t is the a $2n \times 1$ vector of equity prices at time t, V is the variance-covariance matrix of returns, and γ is the fundamental traders' risk-aversion parameter. This equation links price deviations from the rational benchmark (the dividend D_t) to the combined extrapolative demand of within-equity and asset-class switchers.

Fundamental traders face limits to arbitrage that prevent them from pushing risky assets' prices back to fundamentals. Therefore, extrapolators' demand leads to mispricing in the cross section. We differ from Barberis and Shleifer (2003) since we allow mispricing to arise not only as a result of cross-sectional extrapolation but also due to the presence of asset-class switchers. These investors' contribution to cross-sectional mispricing is twofold. First, in good times, both asset-class and within-equity switchers flock to the better-performing stocks, making these stocks even more overvalued than in the absence of asset-class switchers.[17] Similarly, in bad times, both investor types move away from the worst-performing stocks, exacerbating the undervaluation of these stocks. Second, there is an additional impact of asset-class switchers on cross-sectional asset prices in that the added (lower) demand for one group of stocks in good (bad) times contributes to creating larger return differences between stocks in group X and Y. This leads to additional trading by within-equity extrapolators. To investigate the extent of this feedback effect from asset-class switchers to extrapolation in the cross section, we perform an impulse response analysis.

2.1 Impulse Response Functions

Following Barberis and Shleifer (2003), we set some of the driving parameters in the model to the following values: $\psi_M = 0.25$, $\psi_S = 0.5$, $\theta = 0.95$, $\gamma = 0.093$, and $\sigma_\epsilon = 3$. We assume that the price covariance matrix has the same structure as the cash-flow covariance matrix Σ_D. We set $T = 30$, $\boldsymbol{Q} = \boldsymbol{0}$, and $n = 50$, so that there are 100 risky assets in a zero net supply, of which the first 50 belong to group X and the last 50 belong to group Y. At $t = 0$, the initial price of risky assets $D_{i,0}$ is \$50. We examine three cases: a benchmark case in which the aggregate market receives a zero net cash-flow shock, a case in which the market receives a positive fundamental shock, and a case in which the market receives a negative shock. In the benchmark case, the only active extrapolators are within-equity switchers. In the other two cases, asset-class switchers also play a role. In all scenarios, we assume that stocks in group X receive better cash-flow shocks than stocks in Y (i.e., more positive shocks in good times and less negative shocks in bad times). In good times, this causes prices of stocks in X to increase significantly compared to fundamentals, relative

[17] The extrapolative demand from asset-class switchers for good performing stocks is not financed by additional selling or shorting of poor performing stocks. Part of asset-class switchers' capital may even flow to poor-performing stocks. Overall, this extra flow to equities in general, and more flow to better-performing stocks in particular, results in asymmetric price movements leading up to market-wide overvaluation states.

to the stocks in Y, while in bad times, the prices of stocks in Y decrease significantly compared to fundamentals, relative to the stocks in X. Therefore, the stocks in X and Y in the model are the natural counterparts of growth and value stocks, respectively.

The impulse response functions are obtained from a simulation that follows several steps. We set the initial value of V to Σ_D. Then for a given randomly-generated shock, we follow Eq.(22) to calculate the prices of risky assets. This is used to calculate a new price covariance matrix $\hat{V}$. Then we use $\hat{V}$ to calculate a new set of prices for risky assets. We repeat this process until $\hat{V}$ converges. We can achieve convergence for a wide range of parameter choices.

2.1.1 Benchmark Case

Under this scenario, the aggregate market receives a net zero cash-flow shock. Stocks in X receive a positive cash-flow shock, while stocks in Y receive a negative cash-flow shock at $t = 1$, where

$$\epsilon_{i,1} = \kappa,\ \epsilon_{i,t} = 0,\ t > 1,\ \forall i \in X \qquad (23) \qquad \epsilon_{j,1} = -\kappa,\ \epsilon_{j,t} = 0,\ t > 1,\ \forall j \in Y \qquad (24)$$

and $\kappa \geq 0$. In this case, asset-class switchers do not switch between risky assets and cash since they do not observe price movements at the aggregate market level. As a result of the cash-flow shocks, stocks in X have higher returns than stocks in Y, which leads to within-equity switchers buying more of the stocks in X and decreasing their holdings of the stocks in Y. Figure 2 shows the evolution of prices for the aggregate market, $P_{M,t}$, the stocks in X, $P_{X,t}$, and the stocks in Y, $P_{Y,t}$, defined in Eq.(3), after a one-time cash-flow shock with $\kappa = 1$ at $t = 1$.

In the right panel of Figure 2, the good cash-flow news about X pushes its price up to \$51 at $t = 1$. This attracts within-equity switchers' attention and increases their demand for the stocks in group X. The presence of within-equity switchers leads to a substantial deviation of X's price from fundamental value. Similarly, the negative cash-flow news pushes Y's price down to \$49 at $t = 1$, which leads to within-equity switchers moving away from Y and into X. These investors push Y's price further down and away from its fundamental value. Since there is no more cash-flow news afterward, fundamental traders eventually correct prices and bring them back to fundamentals. In the right panel of Figure 2, in the presence of within-equity switchers alone, price deviations from fundamentals are symmetric for X and Y. Thus, at the aggregate level, the market price does not deviate from the fundamental value (left panel). We refer to this as a case of normal market valuation. Therefore, in the benchmark case, mispricing exists only at the level of the cross section of stocks, and not at the aggregate market level. The value premium would be realized as the mispricing is corrected, and both the long and short legs of the strategy contribute equally to the premium.

2.1.2 Overvalued Market

Under this scenario, the aggregate market receives net positive cash-flow news. To accomplish this, both groups X and Y receive a one-time shock at $t = 1$, where

$$\epsilon_{i,1} = \kappa_X,\ \epsilon_{i,t} = 0,\ t > 1,\ \forall i \in X \qquad (25) \qquad \epsilon_{j,1} = \kappa_Y,\ \epsilon_{j,t} = 0,\ t > 1,\ \forall j \in Y \qquad (26)$$

and $\kappa_X + \kappa_Y > 0$.

Since risky assets receive, on average, a net positive cash-flow shock, $\frac{1}{2}(\kappa_X + \kappa_Y)$, the market price, $P_{M,t}$ increases by $\frac{1}{2}(\kappa_X+\kappa_Y)$, which attracts asset-class switchers and increases their demand for risky assets. We set $\kappa_X = 2.5$ and $\kappa_Y = 0.5$. At the aggregate level, the market price increases from \$50 to \$51.5. After observing this, asset-class switchers increase their holdings of risky assets by investing in the better-performing group X. In the cross section, group X has a higher return than group Y as a result of better cash-flow news. Therefore, within-equity switchers buy more of the stocks in X and decrease their holdings of stocks in Y.

Panel A of Figure 3 shows the evolution of prices under this scenario. The left side of the panel shows that, at the aggregate level, the market price increases to \$51.5 at $t = 1$, leading to an increase in asset-class switchers' demand for risky assets. They push the market price even higher and further away from fundamental value. In the absence of any more market-level news, the asset-class switchers gradually lose interest, and the fundamental traders eventually bring the market price to its fundamental value. Since, in this case, the market price reaches a level that exceeds the fundamental value, we refer to this scenario as an overvalued market.

The right side of Panel A of Figure 3 shows price impulse responses in the cross section when both within-equity and asset-class switchers are present (solid lines) and when only within-equity switchers are present (dashed lines). The positive cash-flow news about X and Y push their prices up to \$52.5 and \$50.5, respectively, at $t = 1$ (dotted lines). The relative outperformance of X attracts within-equity extrapolators' attention and increases their demand for X. To finance their additional demand for X, these investors sell some of their holdings in Y. As a result, within-equity switchers push Y's price down and away from fundamental value while they drive X's price even higher. In the presence of asset-class switchers, their additional demand for X creates an even higher increase in X's price, resulting in asymmetric price changes in X relative to Y.

The figure shows that the asset-class switchers are the main drivers of the asymmetric price pattern in X and Y. Within-equity switchers sell Y to buy X, which can only create symmetric price changes, while asset-class switchers use cash to buy X, leading to a much higher price for X. This novel feature of our model captures the idea that the presence of asset-class switchers amplifies the effect of within-equity switchers on prices. This amplification effect comes from the within-equity switchers' additional demand for X after observing its price increase. As a result of the amplification effect, when the price of X reverts back to its fundamental value, the price change is greater than under the benchmark case.

The impulse response functions in Panel A of Figure 3 reveal the first implication of our model for the behavior of the value premium.

Implication 1: The value premium will be higher following states in which the aggregate market is overvalued, compared to cases in which the market has its normal valuation. In addition, the larger the magnitude of overvaluation of the market, a larger correction will be needed for prices to revert back to fundamentals, and therefore, the larger the magnitude of the value premium.

Following an overvalued market, the value premium will be driven mostly by the downward price correction of overvalued stocks that did well in the recent past (i.e., stocks with significantly higher prices relative to fundamentals (growth stocks)).

2.1.3 Undervalued Market

In this case, the aggregate market receives net negative cash-flow news. Both groups X and Y receive a one-time shock at $t = 1$, where

$$\epsilon_{i,1} = \kappa_X,\ \epsilon_{i,t} = 0,\ t > 1,\ \forall i \in X \qquad (27) \qquad \epsilon_{j,1} = \kappa_Y,\ \epsilon_{j,t} = 0,\ t > 1,\ \forall j \in Y \qquad (28)$$

and $\kappa_X + \kappa_Y < 0$.

In this scenario, risky assets receive a net negative cash-flow shock, $\frac{1}{2}(\kappa_X + \kappa_Y)$, and the market price, $P_{M,t}$, decreases to $\frac{1}{2}(\kappa_X + \kappa_Y)$. This induces asset-class switchers to lower their demand for risky assets. We set $\kappa_X = -0.5$ and $\kappa_Y = -2.5$. At the aggregate level, the market price decreases from \$50 to \$48.5, prompting asset-class switchers to leave the market by selling the worse-performing group Y. In the cross section, group X still receives relatively better cash-flow news than Y. As a result, within-equity switchers buy more of X and decrease their holdings of Y.

Panel B of Figure 3 shows the evolution of prices under this scenario. The left side of the panel shows that asset-class switchers observe the decline in the market price at $t = 1$ and decide to decrease their holdings in risky assets. Their outflows cause the market price to decrease even further, deviating from fundamental value. The right side of the panel shows the results in the cross section. In contrast to the case of an overvalued market, asset-class switchers sell Y, resulting in a larger magnitude drop in Y's price than the increase in X's price. The figure shows that asset-class switchers generate a wider price gap between X and Y compared to within-equity switchers. Therefore, in the case of an undervalued market, asset-class switchers amplify within-equity switchers' demand as well. When the price of Y reverts to fundamental value, the price change is larger in magnitude than under the benchmark case.

The impulse response functions in Panel B of Figure 3 reveal the second implication of our model for the behavior of the value premium.

Implication 2: The value premium will be higher following states in which the aggregate market is undervalued, compared to cases in which the market experiences its normal valuation. Furthermore, the larger the magnitude of undervaluation of the market, a larger correction will be needed for prices to revert to fundamentals, and therefore, the larger the magnitude of the value premium. Following an undervalued market, the value premium will be driven mostly by the upward price correction of the worse-performing undervalued stocks (i.e., stocks with significantly lower prices relative to fundamentals (value stocks)).

2.1.4 Simulation of the Value Premium under Market-Wide Misvaluation

We use simulated data to illustrate the implications of the model numerically. We identify better- and worse-performing stocks using a price-to-fundamental ratio, P/F. A stock has performed well if $P/F > 1$, while a stock has performed poorly if $P/F < 1$. We use the same parameter values as in Section 2.1. The simulation results are summarized in Table 1, which examines several scenarios from our model with different levels of market under- or overvaluation.

In Table 1, *Market condition* indicates whether the market is undervalued, normal, or overvalued. *Shock to X* and *Shock to Y* show the cash-flow shocks given to groups X and Y in different scenarios. *Shock to market* is the average of *Shock to X* and *Shock to Y*. If *Shock to market*$= 0$, we define that case as a normal market. If *Shock to market*> 0, we define that case as an overvalued market. If *Shock to market*< 0, we have an undervalued market. *X price deviation* and *Y price deviation* are the maximum of the absolute difference between price and fundamental value for X and Y, respectively. *X return (%)* is calculated as $\frac{P_{X,T}-P_{X,t}}{P_{X,t}}$, where t is the time when X's price reaches its peak, and T is the terminal date. *Y return (%)* is calculated as $\frac{P_{Y,T}-P_{Y,t}}{P_{Y,t}}$, where t is the time when Y's price reaches its bottom, and T is the terminal date. *Premium (%)* is the difference between *Y return (%)* and *X return (%)*. Time t is the time when the price of X reaches its peak and the price of Y reaches its bottom.

The results indicate that, in normal times, the premium is 1.02%, emanating from within-equity switching. The premium is much larger when the aggregate market has deviated from fundamental value. After the aggregate market receives a shock of \$1.5 per share, the value premium is 2.04%. On the other hand, after the aggregate market receives a shock of -\$1.5 per share, the premium is 2.35%. Furthermore, following an overvalued market, the premium mostly results from the relative underperformance of stocks in X. Following an undervalued market, the premium is mostly driven by the relative outperformance of stocks in Y.

3 Methodology and Results

In this section, we show that the magnitude of the value premium varies conditional on the state of market-wide valuation. In particular, we show that the value premium is larger following market-wide over- and undervaluation. Our analysis contains two steps. We first construct a measure of market-wide misvaluation based on B/M ratios. Then, we document the performance of the value premium following periods of market-wide over- and undervaluation.

3.1 Data

The sample period for our main analysis is January 1968 to December 2018. Monthly stock returns are obtained from the Center for Research on Securities Prices (CRSP). We follow standard conventions and restrict the analysis to common stocks (Share Codes 10 and 11) of firms listed in the U.S. and traded on NYSE, Amex, or Nasdaq. Monthly returns are adjusted for delisting.[18] We exclude stocks with prices less than \$1, financial firms, and utility firms.

The accounting data is from the Standard and Poor's Compustat database. Book equity is calculated as the book value of stockholders' equity, plus balance sheet deferred taxes and investment

[18] If the delisting return is missing and the delisting is performance-related, we impute a return of -30% for NYSE and Amex stocks (Shumway (1997)) and -55% for Nasdaq stocks (Shumway and Warther (1999)).

tax credit (if available), minus the book value of preferred stock. Depending on availability, we use redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock.[19] We use the shareholders' equity number as reported by Compustat. If this data is not available, we calculate shareholders' equity as the sum of common and preferred equity. If neither is available, we define shareholders' equity as the difference between total assets and total liabilities. Based on Asness and Frazzini (2013), we compute book-to-market ratios (B/M) on a monthly basis, where we use book equity from the last fiscal year end and update market value at the end of each month. Book equity is updated annually, at the end of each June.

3.2 A Measure of Market-wide Misvaluation

We begin by constructing a measure of market-wide valuation based on B/M. The market-wide B/M ratio is computed as the cross-sectional average of individual stocks' B/M ratios.[20] To identify periods of market-wide under- or overvaluation, we use a data-driven and recursively-updated approach that does not suffer from a look-ahead bias. Specifically, for each month t, we obtain the past 10 years of the time series of market-wide B/M ratios from $t-120$ to $t-1$. We then find the percentile standing of the market-wide B/M ratio at time t in the historical distribution of market-wide B/M ratios over the last 10 years. We refer to this measure as relative market-wide valuation, denoted as RMV. The values for the RMV measure are in the interval (0,1). We use the tails of the RMV variable to identify periods of *significant* market-wide misvaluation. For example, if the current market-wide B/M is in the bottom 5% of the historical benchmark distribution, we denote that as $RMV_{0.05}$ and designate it as a period of market-wide overvaluation. If the most recent market-wide B/M is in the top 5% of the historical distribution, we denote that as $RMV_{0.95}$ and designate it as a period of market-wide undervaluation.[21] Therefore, the subscript of RMV represents the placement of the most recent market-wide B/M ratio in the recursively estimated historical benchmark distribution. We define normal times as instances in which the current market-wide B/M ratio is not in the tails of its historical distribution and denote them as RMV_{normal}. In summary, rather than using pre-specified filters to define misvaluation, we let the historical data drive the definition of market-wide valuation states.

Figure 4 plots the time series of RMV over the entire sample period, together with NBER recession periods. Higher (lower) levels of RMV correspond to market-wide undervaluation (overvaluation). The figure shows that our measure of market-wide valuation lines up with historical periods during which the market has been described as over- and undervalued. For example, the low values of RMV in the buildup to the Tech Bubble period correspond to states of market

[19] Ken French's website states "Because of changes in the treatment of deferred taxes described in FASB 109, files produced after August 2016 no longer add Deferred Taxes and Investment Tax Credit to BE for fiscal years ending in 1993 or later." We adjust the calculation for book equity based on FASB 109 after 1993.

[20] The market-wide B/M ratio is inversely related to the state of market-wide valuation, i.e., very large (small) B/M ratios correspond to market-wide undervaluation (overvaluation). When computing the market-wide B/M ratio, we winsorize at 1% and 99%, and exclude firms with negative B/M ratios.

[21] For robustness, we use the 5th, 10th, 20th, 80th, 90th, and 95th percentiles of the historical distribution of the market-wide B/M to define the tails of the distribution.

overvaluation. The gradual increase in the values of RMV during the recent Great Recession indicates that the market was undervalued by the end of the recession and subsequently experienced a correction. It is interesting to note that while the RMV measure tends to spike during NBER recessions, periods of undervaluation happen during expansions as well. This suggests that RMV contains information independent of the business cycle as measured by NBER recessions.

Another potential measure of market-wide misvaluation is the market's P/E ratio, which is equivalent to the value-weighted average of individual stocks' P/E ratios. We do not use this measure because: (i) it is dominated by the valuation ratios of a few mega-cap stocks, (ii) contrary to the equal-weighted average, and probably because of (i), the value-weighted valuation ratio does not exhibit mean reversion at horizons of up to one year (please refer to Table IA1 in the Internet Appendix), making it difficult to come up with a benchmark for normal valuation.[22] Moreover, since we are measuring the value premium using equal-weighted portfolio returns, using equal weighting to measure market-wide misvaluation is internally consistent. Nevertheless, when we use the market's P/E ratio (measured as the value-weighted P/E ratio of individual stocks) and classify value and growth stocks using P/E sorts, we find that the value-weighted value premium is significant only following states of market-wide misvaluation. As expected, the pattern is weaker compared to equal-weighted results.

3.3 Value Premium Conditional on Market-Wide Misvaluation

Within the framework of the model in Section 2, RMV can be viewed as a signal which indicates when extrapolators have been active for a while in pushing prices away from fundamental values. Therefore, we should be able to observe that (i) periods of significant market-wide misvaluation are associated with significant misvaluation of growth or value stocks and (ii) significant price corrections in the data follow extreme market-wide valuations. In this section, we examine the performance of the value premium conditional on three market-wide states: overvaluation, undervaluation, and normal times, as measured by RMV.

Table 2 reports monthly equal-weighted portfolio returns for value stocks, growth stocks, and the value premium following scenarios with different degrees of market-wide misvaluation. The average returns of these portfolios are reported for one month and 12 months following market-wide misvaluation. The table also shows the average market-wide B/M ratio in each valuation scenario and the value spread. The value spread is the difference between the natural logarithm of B/M for value and growth portfolios, and we calculate it following Cohen, Polk, and Vuolteenaho (2003). The sample period is from 1968 to 2018.

Table 2 shows that, following periods with extreme market-wide overvaluation, the value premium is large and significant. For example, when the recent average B/M ratio is in the bottom 10% of the benchmark distribution ($RMV_{0.10}$), the value premium is on average 1.70% per month during the first month after portfolio formation (t-statistic=4.30) and on average 1.22% per month

[22] The analysis in Greenwood and Shleifer (2014) suggests that market-wide investor expectations fully mean-revert at the yearly horizon. Thus, we argue that RMV can be a more appropriate metric within our framework.

over the 12 months after portfolio formation (t-statistic=4.05). The table shows that as the degree of market-wide overvaluation increases (RMV going from 0.20 to 0.05), the magnitude of the value premium increases as well.

Following periods with extreme market-wide undervaluation, the value premium is also large and significant. For example, for $RMV_{0.90}$, the value premium is on average 3.42% per month in the first month after portfolio formation (t-statistic=4.15) and on average 2.80% per month over the 12 months after portfolio formation (t-statistic=4.80). As the degree of market-wide undervaluation increases (RMV going from 0.80 to 0.95), so does the value premium.

Overall, the results in Table 2 reveal that the value premium is larger following periods with extreme market-wide valuations. This evidence suggests that the unconditional value premium is largely accounted for by the periods in which market prices deviate significantly from fundamentals.

Table 2 also shows that the value spread in undervalued market states is higher than under normal valuation states. However, the value spread is lower in market-wide overvaluation states than it is in normal valuation states. This suggests that the results in Table 2 based on RMV are distinct from existing results which show that the value spread has predictive power for the value premium (e.g., Cohen, Polk, and Vuolteenaho (2003)).

It is interesting to note that, following normal valuation levels for the market, the value premium based on equally-weighted returns is not statistically significant one month after portfolio formation. The average value premium over the 12 months after portfolio formation is 0.60% and statistically significant. However, this magnitude is the smallest compared to all other states of market-wide misvaluation. In the case of using value-weighted portfolio returns (results are reported in Table IA3 of the Internet Appendix), the value premium is not significantly different from zero following normal valuation states for one month and 12 months after formation. These results suggest that the unconditional profitability of the value strategy documented previously in the literature is primarily driven by extreme market-wide misvaluation states. This is in line with arguments that suggest that the value premium is an artifact of mispricing.

We also examine the valuations of value and growth stocks in different states of market-wide misvaluation. Our model implies that in states of market-wide overvaluation, growth stocks will be significantly overpriced, while in states of market-wide undervaluation, value stocks will be significantly underpriced. To assess the degree of misvaluation at the stock level, at each point in time, we use the historical pooled cross-sectional distribution of firm-level B/M ratios as the valuation benchmark. Then, in each month t, we examine whether stocks that are currently classified as value or growth based on a relative cross-sectional sort are under- or overvalued based on the benchmark historical distribution of valuation ratios. Specifically, in each month t, we obtain the breakpoint ranking of value and growth stocks' valuations relative to the historical benchmark. Table 2 shows that in states of extreme market-wide overvaluation ($RMV_{0.10}$), growth stocks' B/M ratios are in the bottom 10% of the historical benchmark distribution (i.e., all stocks in this portfolio are located in the lowest 10.6% tail of the benchmark distribution of stock-level B/M ratios), while value stocks' B/M ratios are in the top 26% (1-0.737) of the historical benchmark distribution. In states of extreme market-wide undervaluation ($RMV_{0.90}$), growth stocks' B/M ratios are in the bottom 16.3% of the historical benchmark distribution, while value stocks' B/M ratios are in the top 6.3% (1-0.938) of the historical benchmark distribution. Therefore, when the aggregate market is overvalued, growth stocks are significantly overvalued, but value stocks' valuations are not extreme relative to historical standards. Similarly, when the aggregate market is undervalued, value stocks are significantly undervalued but growth stocks' valuations are not extreme relative to historical standards. In states of normal market valuation (RMV_{normal}), value and growth stocks are not significantly misvalued according to their benchmark distribution.

Following the asymmetry in value and growth stocks' mispricing in different market-wide valuation states, we expect that the value premium will be driven by different types of stocks following market-wide under- or overvaluation. In Table 3, we examine the types of stocks that drive the value premium following different states of market-wide misvaluation. The table reports the average returns of 10 B/M decile portfolios over the 12 months following different market-wide misvaluation scenarios. To the extent that Decile 5 represents the performance of the average stock, the value premium could be examined in the context of value and growth stock return deviations with respect to the average stock. Results in Table 3 are consistent with the conjecture that the value premium is driven by the correction of growth stocks' extreme overvaluation following market-wide overvaluation and value stocks' extreme undervaluation following periods of market-wide undervaluation. For example, following market-wide overvaluation ($RMV_{0.10}$), the difference between the returns of growth stocks and those of Decile 5 is 0.83% (-0.28% - 0.55%) per month. On the other hand, the difference between the returns of value stocks and those of Decile 5 is 0.39% (0.94% - 0.55%) per month. Therefore, growth stocks severely underperform relative to the average stock and drive the realized return of the value premium (1.22%).

Following market-wide undervaluation ($RMV_{0.90}$), the difference between the returns of value stocks and those of Decile 5 is 1.94% (3.63% - 1.69%) per month. On the other hand, the difference between the returns of growth stocks and Decile 5 is -0.86% (0.83% - 1.69%) per month. Therefore, value stocks outperform relative to the average stock and drive the realized return of the value premium (2.80%).

In Table 4, we report Jensen's alphas for value stocks, growth stocks, and the value premium following different market-wide misvaluation scenarios. The table shows alphas for one month and 12 months following misvaluation. The results in Table 4 using risk-adjusted returns are similar to the findings in Table 2. For example, following $RMV_{0.10}$, the next-month alpha of the value premium is 1.72% (t-statistic=4.60) and the average 12-month alpha is 1.21% (t-statistic=9.09). As the degree of market-wide overvaluation increases (RMV going from 0.20 to 0.05), the magnitude of alpha increases as well. Furthermore, following $RMV_{0.90}$, the next-month alpha of the value premium is 3.45% (t-statistic=4.21) and the average 12-month alpha is 2.98% (t-statistic=10.98). As the degree of market-wide undervaluation increases (RMV going from 0.80 to 0.95), so does the alpha of the value premium (except in the case of the next-month alpha when $RMV_{0.90}$). Table 4 further shows that, following normal times for the market (RMV_{normal}), the next-month alpha of the value premium is not statistically significant. Following normal times, the average alpha of the value premium over the next 12 months is 0.54% and statistically significant.

The risk-adjusted returns of the value premium following different RMV levels are also consistent with the proposition that the value premium stems mostly from the price correction of growth (value) stocks following an overvalued (undervalued) market. For example, in Table 4, the difference between the alpha of value stocks one month after $RMV_{0.10}$ and the alpha of value stocks one month after normal valuation is 0.64% (1.10% vs. 0.46%). For growth stocks, this difference is -0.97% (-0.62% following $RMV_{0.10}$ vs. 0.35% following normal valuation). The difference between 0.64% and -0.97% based on GMM is statistically significant with a χ^2 statistic of 10.84 (p-value=0.0010). Therefore, relative to normal times, growth stocks' alpha depreciates significantly more than value stocks' alpha following market overvaluation.

On the other hand, in Table 4, the difference between the alpha of value stocks one month after $RMV_{0.90}$ and the alpha of value stocks one month after normal valuation is 2.78% (3.24% vs. 0.46%). For growth stocks, this difference is -0.55% (-0.20% following $RMV_{0.90}$ vs. 0.35% following normal valuation). The GMM test for the significance of the difference between 2.78% and -0.55% has a χ^2 statistic of 8.68 (p-value=0.0032). The results show that value stocks' alpha appreciates significantly more than growth stocks' alpha following market undervaluation. Similar results hold for the other values of RMV and for average alpha over the 12 months following misvaluation.

The results so far show that our measure of market-wide misvaluation, RMV, is a significant predictor of the magnitude of the value premium. Next, we perform a multiple regression analysis to test whether our results are robust to including other variables that have been shown to predict the value premium. For example, previous studies examine the profitability of value investing conditional on the spread in valuation multiples between value and growth portfolio, i.e, the value spread (Cohen, Polk, and Vuolteenaho (2003), Asness et al (2000), Asness et al (2021)). They find that the expected returns of value-minus-growth strategies are higher when the value spread is wider. The value spread is different from our RMV measure. The RMV measure captures the extent to which market-wide valuation shifts relative to the historical benchmark. It distinguishes periods of under- and overvaluation from normal market-wide valuation periods. In addition, we control for other potential predictors of the value premium, including market volatility, the Sentiment Index of Baker and Wurgler (2006), a dummy variable for NBER recessions, the equal-weighted average of individual B/M ratios, the risk-free rate, the yield spread between the 10-year and 1-year Treasury bond (TERM spread), the yield spread between the Baa and Aaa corporate bond (DEF), and the dividend yield of the market portfolio (DIV).[23]

Our measure of market-wide misvaluation, RMV, is such that its extremely low or high values are positively associated with the subsequent value premium. To retain this characteristic of RMV in a regression specification, we replace it with a variable called the degree of market misvaluation,

[23] We obtain the investor sentiment index from Jeffrey Wurgler's website. and the data on bond yield from the website of the Federal Reserve Bank of St. Louis.

DOM, as $(RMV - 0.5)^2$ and examine the following specification:

$$Value\,premium_{t,t+h} = b_0 + b_1 * DOM_t + b_2 * Value\,spread_t + b_3 * X_t + \epsilon_{t,t+h}, \tag{29}$$

where the dependent variable is the future h-month value premium, DOM is $(RMV - 0.5)^2$, $Value\,spread$ is the difference between the log B/M of value and growth stocks, and X is a vector of other control variables.[24]

Table 5 presents results for horizons $h = 3, 6, 12$ months. The table shows that the predictive ability of DOM, which is a function of the magnitude of RMV, for the future profitability of value-minus-growth is economically and statistically significant by itself and also after controlling for value spread and other variables described above.[25] This holds for all return horizons. The predictive ability of the value spread is sensitive to the inclusion of other control variables. For example, the value spread is not a significant predictor of the 3-month and 6-month value premium in the presence of other control variables. Overall, the results in Table 5 suggest that RMV is distinct from the value spread and other predictive variables. It contains independent predictive power for the future performance of the value premium.

3.4 Value Investing Based on Market-Wide Misvaluation

This section complements our earlier findings by asking how much an investor would benefit from a dynamic value strategy conditional on market-wide misvaluation. The first strategy that we consider, DYNVALUE_1, implements value-minus-growth in a given month if RMV at the end of the previous month is either high ($RMV_{0.80}$) or low ($RMV_{0.20}$), and holds the 1-month T-bill otherwise. The second strategy, DYNVALUE_2, holds the value-weighted market portfolio (rather than T-bill) for intermediate RMV values. We quantify benefits to the investor by computing mean portfolio returns, return volatility, and Campbell and Thompson (2008) utility gains. Further details about the construction of the two strategies are provided in the Internet Appendix.

Figure IA1 in the Internet Appendix shows that an investor who trades the dynamic value strategies based on RMV signals receives not only higher mean returns but also lower risk. Higher average returns and lower volatility translate into large utility gains for a hypothetical mean-variance investor who trades on value conditional on market-wide misvaluation.

4 Mechanism: Empirical Evidence

In this section, we provide evidence in support of the theoretical mechanism and the assumptions underlying our model. We first document the behavior of cash-flow news and capital flows to equities leading up to market-wide misvaluation. Then we explore the return extrapolation channel in more

[24] We measure the deviation of RMV from 0.5 since 0.5 represents states of normal market valuation. We use squared deviation to better capture the impact of extreme misvaluation periods. We also use an alternative measure defined as $|RMV - 0.5|$ and get similar results.

[25] We obtain comparable results when using $|RMV - 0.5|$ to define DOM. For example, in Table 4, using $h = 3$ and controlling for other variables, the coefficient of DOM measured by $(RMV - 0.5)^2$ is 11.93 with a t-statistic of 5.32. When we use DOM measured by $|RMV - 0.5|$, the coefficient of DOM is 6.04 with a t-statistic of 4.87. Similar results hold for $h = 6, 12$.

detail using data on extrapolative beliefs about the aggregate market return and investor return expectations about individual stocks.

4.1 Cash Flows Leading up to Market-wide Misvaluation

In our model, when the aggregate market experiences good (bad) cash-flow news, this news tends to be disproportionately concentrated in growth (value) stocks. To investigate whether this assumption is consistent with the data, we use standardized unexpected earnings, SUE, as a proxy for cash-flow shocks. Following Bernard and Thomas (1989), we compute unexpected earnings as the difference between realized earnings and the median forecast of earnings from I/B/E/S, scaled by the standard deviation of unexpected earnings estimated over the previous 20 quarters.

We compute the SUE of value and growth portfolios as the median SUE of stocks within each portfolio. We then track SUE for value and growth portfolios over the 12 months leading up to market-wide misvaluation.[26] We also track the SUE of Decile 5 (D5) in the set of portfolios sorted by B/M as a proxy for the SUE of the average stock.

Results are presented in Table 6. Unconditionally, value stocks experience negative earnings surprises while growth stocks experience positive earnings surprises during the year before portfolio formation.[27] Leading up to market-wide undervaluation, value stocks have more extreme negative SUE than under normal times and compared to the SUE of the average stock (D5). For example, going from normal to undervalued times ($RMV_{0.95}$), the SUE of value stocks goes from -0.11 to -0.18, while the SUE of the average stock goes from 0.06 to -0.01. Growth stocks keep experiencing smaller but positive SUE leading up to undervaluation. On the other hand, leading up to significant market-wide overvaluation, growth stocks have higher SUE than under normal times and compared to the SUE of the average stock. For example, going from normal to overvalued times ($RMV_{0.05}$), the SUE of growth stocks increases from 0.09 to 0.17, while the SUE of D5 increases from 0.06 to 0.11. The SUE of value stocks stays negative, albeit smaller in magnitude.

Overall, the results land support to our model assumption that growth stocks experience large positive cash-flow shocks leading up to market-wide overvaluation, while value stocks experience large negative cash-flow shocks leading up to market-wide undervaluation.

4.2 Fund Flows Leading up to Market-Wide Misvaluation

In our model, the existence of asset-class switchers implies that periods leading up to market-wide overvaluation (undervaluation) are associated with higher inflows (outflows) to (from) equity. To investigate whether some investors' demand for stocks is consistent with such asset-class switching, we use data on fund flows from the Investment Company Institute (ICI). We compute fund flows to domestic equity and bond funds leading up to market-wide undervaluation, overvaluation, and normal valuation states.[28] To reduce the impact of a few very large monthly flows, we use 6-month

[26] The sample period is from 1988 to 2018 due to data availability from I/B/E/S.

[27] This is consistent with previous results reported by Fama and French (1995).

[28] ICI data on asset-class level flows was made available to us by Azi Ben-Rephael for the period ending in 2015. We construct domestic equity flows by aggregating dollar flows to five equity fund types: growth, aggressive growth,

cumulative flows and focus on median flows across different market-wide misvaluation states.[29]

States of market-wide misvaluation at time t are based on RMV. A value of RMV lower than 0.25 indicates market-wide overvaluation, while a value higher than 0.75 indicates market-wide undervaluation. When RMV is between these two levels, the market has normal valuation.[30]

On the left side of Figure 5, we plot flows to domestic equity and bond funds in the run-up to different valuation states over the period from 2000 to 2018. In the right portion of the figure, we plot the abnormal component of fund flows leading up to undervaluation or overvaluation states. The abnormal component of flows is defined as the difference between fund flows in misvaluation states and fund flows in normal valuation states. Overall, the inflows (outflows) into (from) equity observed in the run-up to market-wide over(under)valuation are consistent with the dynamics of asset-class switchers' demand in our model.

4.3 Extrapolative Beliefs and the Value Premium

In our model, (over)extrapolative expectations formation is the main behavioral mechanism driving the value premium. In this section, we provide evidence in support of this channel. We do so by using four different approaches. First, we extract extrapolative beliefs from survey data which elicits expectations about future stock market returns.[31] Using this data, we show that, consistent with our proposed mechanism, the value premium is particularly strong following states in which the market is overvalued (undervalued) and aggregate extrapolative beliefs are particularly optimistic (pessimistic). Second, we study extrapolative expectations in the cross-section of stocks across states of market misvaluation using data from stock-picking contests collected in an online crowdsourcing platform, Forcerank. This analysis allows us to investigate whether extrapolative expectations formation for growth and value stocks is indeed time-varying as in our model.

Third, we test if individual stock return expectations implied from analysts' price target revisions are extrapolative toward value and growth stocks and whether this behavior is stronger leading up to market-wide misvaluation states. Finally, we complement the analysis of beliefs summarized above with an analysis of investor trading behavior. To this end, we use stock-level order imbalance data to test the extent to which buying/selling demand for value and growth stocks depends on the past return of these stocks and whether this dependence is stronger leading up to market-wide misvaluation states.

income&growth, income equity, and sector (e.g., Ben-Rephael, Kandel, and Wohl (2012)). Bond flows are obtained by aggregating flows to corporate bonds, global bonds, high yield bonds, MBS, national municipal bonds, state municipal bonds, and stratified income bonds. Following prior literature (e.g., Sirri and Tufano (1998)), we calculate flows as the ratio of dollar flows and lagged total net asset value (TNA). Dollar flows are the sum of "new sales" minus "redemption" plus "exchanges in" minus "exchanges out", aggregated across fund types whenever applicable. TNA is the sum of assets under management across the relevant fund categories.

[29] Gabaix and Koijen (2021) note that flows are non-stationary. Therefore, we extract the stationary component of flows by implementing a procedure outlined in Hamilton (2018)

[30] Due to the availability of flow data over a shorter window, we use 25^{th} and 75^{th} percentile of the distribution of RMV as cut-off points instead of more extreme cutoffs.

[31] In our model, aggregate extrapolative beliefs proxy for asset-class switchers' beliefs about the market.

4.3.1 Extrapolative Beliefs About the Market Return: Survey-based Evidence

Our model implies that investors become overly optimistic about growth stocks when extrapolative beliefs about the market are also optimistic, and they become overly pessimistic about value stocks when beliefs about the market are also pessimistic. To test this prediction we identify states of the world that are associated with extreme values of RMV and extreme extrapolative beliefs.

Several recent papers argue that investor extrapolative beliefs can be recovered from survey data on expectations about the aggregate market return (e.g., Greenwood and Shleifer (2014), Barberis et al (2015), Cassella and Gulen (2018, 2019)). We follow this work and extract extrapolative beliefs about market returns from survey data. The data comes from Gallup, the American Association of Individual Investors (AAII), and the Investor Intelligence (II) survey. Using these three surveys, we create a long time series of investor expectations.[32] We refer to this as SURVEY_t. To identify the variation in investor beliefs about the market return that is driven by extrapolation, we follow Greenwood and Shleifer (2014) and extract the extrapolative component of SURVEY_t by regressing survey-based expectations on a weighted sum of past stock market returns with exponentially decaying weights:

$$\text{SURVEY}_t = a + b\sum_{j=1}^{N} w_j R_{(t-j+1)} + \epsilon_t, \qquad w_j = \frac{(\lambda)^{(j-1)}}{\sum_{k=1}^{N}(\lambda)^{(k-1)}} \tag{30}$$

where N is equal to 15 and $R_{(t-j)}$ is the annual return of the market j years in the past. The fitted value from Eq.(30) is our measure of extrapolative beliefs, denoted as $EXPX$. The advantage of $EXPX$ is that it is designed to capture not only the basic notion of a positive relation between beliefs and past returns but also the tendency of investors to overweight recent returns compared to more distant ones. This relative weighting is considered a key feature of extrapolation (Barberis (2018)), and it is an important assumption in our model (see Eq.(11)). It is also consistent with the structural parameters of extrapolative beliefs formation that characterize extrapolation in the surveys.

As expected, RMV and $EXPX$ exhibit a negative correlation of -0.60, i.e., when extrapolative beliefs about the future market return are high, RMV is low, indicating market-wide overvaluation. The high negative correlation is consistent with the notion that the presence of extrapolators has an impact on market-wide misvaluation. On the other hand, the lack of perfect correlation between RMV and $EXPX$ indicates that there are other sources of variation in RMV. Thus, conditioning on both market-wide misvaluation based on valuation ratios and extrapolative beliefs from surveys can provide a sharper focus on the extrapolation channel behind the value premium.[33]

We perform independent sorts based on RMV and $EXPX$. We split the sample into 3 pe-

[32] This time series is obtained as an average of consensus expectations (bullish minus bearish) from Gallup, AAII, and II, each converted to the quantitative form using a procedure described in Greenwood and Shleifer (2014). Whenever only a subset of these surveys is available, the available surveys are used to calculate the average.

[33] Nagel and Xu (2021) point out that aggregate valuation ratios are much more persistent than extrapolative beliefs about returns from surveys, indicating that drivers other than return extrapolation can also play a role in market-wide misvaluation.

riods according to RMV - overvaluation ($RMV_{0.20}$), normal (RMV_{normal}), and undervaluation ($RMV_{0.80}$). Independently, we split the sample into 3 periods based on $EXPX$ - high expectations ($EXPX_{high}$, for $EXPX$ being above its full-sample 80th percentile), normal expectations ($EXPX_{normal}$, for $EXPX$ being between its full-sample 20th and 80th percentiles), and low expectations ($EXPX_{low}$, for $EXPX$ being below its full-sample 20th percentile). Periods leading up to overvaluation that are also associated with significantly optimistic beliefs are characterized by $RMV_{0.20}$ and $EXPX_{high}$. Similarly, periods leading up to undervaluation with pessimistic beliefs about the market are characterized by $RMV_{0.80}$ and $EXPX_{low}$. Finally, we retain normal RMV states as the benchmark case.

In Panel A of Table 7, we report the average returns of value and growth stocks over the 12 months leading up to market-wide misvaluation. We specifically focus on the periods characterized by both extreme misvaluation and extreme extrapolative beliefs. The results suggest that growth stocks have large positive returns leading up to market-wide overvaluation when expectations about the future market return are extremely high ($RMV_{0.20}$, $EXPX_{high}$). Value stocks have large negative returns leading up to market-wide undervaluation when expectations about the future market return are extremely low ($RMV_{0.80}$, $EXPX_{low}$).

To the extent that the pre-formation returns of value and growth stocks in Table 7 are due to incorrect extrapolative beliefs, we should be able to detect these mistakes in the form of predictable return dynamics post-formation. Therefore, we track the returns of value and growth stocks following states of market-wide misvaluation and extreme extrapolative expectations.

In Panels B and C of Table 7, we report the average returns of value and growth stocks one month and 12 months after states of market-wide misvaluation and extreme extrapolative expectations. Following overvaluation ($RMV_{0.20}$, $EXPX_{high}$), growth stocks experience a reversal and their returns become negative. This results in a large value premium. It is interesting to note that the value premium is larger following these states, as opposed to states that just display overvaluation based on $RMV_{0.20}$ (Table 2). For example, following overvaluation as defined by $RMV_{0.20}$ and $EXPX_{high}$, the value premium is 1.91% per month one month after formation and 1.71% per month twelve months after formation. For comparison, following overvaluation as defined by $RMV_{0.20}$ alone, the value premium is 1.49% one month after formation and 1.12% twelve months after formation. The finding that the value premium is larger and driven predominantly by growth stocks when the market is overvalued and investors have extreme extrapolative beliefs provides strong support for the mechanism of our model.

Moving on to market-wide undervaluation, the value premium is larger following states with $RMV_{0.80}$ and $EXPX_{low}$ vs following states with just $RMV_{0.80}$ (Table 2). For example, following undervaluation as defined by $RMV_{0.80}$ and $EXPX_{low}$, the value premium is 3.57% per month one month after formation and 3.00% per month twelve months after formation. For comparison, following undervaluation as defined by $RMV_{0.80}$ alone, the value premium is 2.91% one month after formation and 2.56% twelve months after formation. This evidence is consistent with the conjecture that extrapolative expectations about the stock market play a role in the conditional behavior of the value premium.

Even though our measure of extrapolative beliefs, $EXPX$, is derived from beliefs about the stock market return, in this section, we assume that the tendency to extrapolate returns applies more broadly to different assets that belong to similar investment categories (e.g., individual stocks vs. a portfolio of stocks). We argue that periods of high $EXPX$ capture not only extrapolative behavior regarding market returns but also extrapolation of individual stock returns.

4.3.2 Extrapolative Beliefs in the Cross Section: Evidence from Forcerank

Previously, we find that the value premium following overvaluation is mainly driven by the declining returns of growth stocks, while the premium following undervaluation is mainly driven by the increasing returns of value stocks. To the extent that post-formation returns capture corrections in (over)extrapolative expectations, we expect to see stronger extrapolation behind growth stock returns in periods leading up to overvaluation and stronger extrapolation behind value stock returns in periods leading up to undervaluation.

To examine this possibility, we follow Da, Huang, and Jin (2021) (DHJ), who study expectations formation in the cross section of U.S. stocks using data from an online crowdsourcing platform called Forcerank. The platform organizes weekly contests in which individuals are asked to rank 10 stocks based on their expectations of stock returns over the following week. Stocks that are ranked higher in terms of future performance are assigned higher scores. Like DHJ, we use stocks' average score in a contest that ends in week t as a proxy for investors' consensus expectations at time t about stock returns over week $t+1$. We refer to the time t consensus expectation of the future return of stock i as CE_{it}. To analyze investors' extrapolative expectations in the cross section, we adopt DHJ's extrapolation model, reported below:

$$CE_{it} = \gamma_0 + \sum_{s=0}^{11} \beta_s * R_{i[t-s-1,t-s]} + \epsilon_{it}. \tag{31}$$

In the model, investors form expectations about future 1-week returns based on returns in the 12 weeks prior to expectations formation, up to and including the return in the week in which investors post their scores to the Forcerank platform.

We focus on contests that refer to the prediction of future returns and contest categories outlined in DHJ. We ensure that consensus expectations are regressed on returns that investors have observed prior to submitting their ranking to Forcerank. To this end, we measure consensus expectations based on forecasts submitted to Forcerank only by those investors who observe stock returns ending in week t. Since the vast majority of contests begin on Monday morning of week $t+1$, we can then use calendar trading-week returns in weeks $t-11$ to t as the right-hand-side variables in Eq.(31).

Whereas DHJ document return extrapolation in the cross section at large, we are interested in whether return extrapolation can help explain the dependence of the value premium on market-wide misvaluation. Thus, we estimate Eq.(31) separately for value and growth stocks. We are interested in comparing the average strength of return extrapolation to the strength of return extrapolation leading up to market-wide overvaluation. Therefore, we study the magnitude, sign, and significance of the β_s in Eq.(31) for value and growth stocks in different market valuation states to the extent allowed by the short sample we have.[34]

The results of our analysis are in Table 8, which reports estimates of the individual coefficients from Eq.(31). First, we report full-sample results for all stocks and separately for value and growth stocks without conditioning on market valuation. Then we analyze expectations leading up to market-wide overvaluation. The bottom of the table summarizes the sensitivity of expectations to past returns by reporting the sum of β_s for the most recent four weeks (Month t), for the two previous months (Month $t-1$ and Month $t-2$), and for the entire 12-week window (*Total*).

The first column in Table 8 is consistent with the evidence reported in DHJ. In particular, return expectations in the cross section are positively related to past stock returns, with a larger sensitivity of expectations to recent returns as opposed to distant returns. Columns (2) and (3) show that, on average, the sensitivity of expectations to past returns is larger for growth stocks than value stocks. This is true for individual coefficients, as well as the cumulative coefficients reported at the bottom of each column.

To investigate the cross-sectional differences in extrapolation between value and growth stocks in periods leading up to market-wide overvaluation, we use consensus expectations for contests occurring 6 months prior to an overvalued market state. The results are presented in the last three columns of Table 8. The results are striking and provide strong support for our conjecture that growth stocks experience stronger return extrapolation leading up to market-wide overvaluation. In particular, extrapolation among growth stocks, measured as the overall dependence of expectations on past returns, becomes stronger leading up to overvaluation. The sum of the coefficients rises from 14.190 for Growth in the full sample to 21.351 leading up to overvaluation. However, the same is not true for value stocks, whose sensitivity to past returns declines from 7.204 unconditionally to 0.898 leading up to overvaluation. The main finding in Table 8 is that the heterogeneity in expectations formation between value and growth stocks increases leading up to overvaluation. The stronger return extrapolation for growth stocks is consistent with extrapolation being the driving force behind the significant mispricing of growth stocks in the run-up to overvaluation, ultimately resulting in a stronger subsequent value premium.

To test whether the documented differences in extrapolation over time and across value and growth stocks are statistically significant, we estimate the following linear probability model with

[34]The sample period is from February of 2016 to February of 2018, which mostly consists of normal and overvalued market states as defined by RMV. Our definition of value and growth is based on a stock's book-to-market ratio in the month ending prior to week t. Although the sample is large, with about 1000 distinct contests, we note a strong tilt toward growth stocks. Thus, to guarantee that a sufficient number of stocks fall both in the value and growth portfolios, we use top and bottom 30% cut-off points for B/M at the end of week t. Moreover, the short time span and the variation in market-wide misvaluation that we observe in the sample do not allow us to study expectations formation leading up to undervaluation. Thus, we only focus on comparing expectations formation in the cross section in normal times versus months leading up to market-wide overvaluation.

a triple interaction term:

$$\begin{aligned} I(High)_{ijst} &= c * R_{jt} * I(Stock\_Type_{jt}) * I(Overval_t) + b_1 * R_{jt} + b_2 * I(Stock\_Type_{jt}) \\ &+ b_3 * I(Overval_t) + d_1 * R_{jt} * I(Stock\_Type_{jt}) + d_2 * R_{jt} * I(Overval_t) \\ &+ d_3 * I(Stock\_Type_{jt}) * I(Overval_t) + \alpha_j + \alpha_s + \epsilon_{ijst} \end{aligned} \tag{32}$$

where i indexes Forcerank forecasters, j indexes a given stock, s indexes a given contest, t indexes time, and *Stock_Type* is either Value or Growth. The left-hand side variable is a dummy variable that takes a value of 1 when the forecaster assigns a rank of 1 to 5 to the stock, i.e., the forecaster places the stock at the top of the distribution of future returns. Given that the forecaster who participates in a contest s involving stock j ranks stocks in the contest with values from 1 to 10, we interpret any rank equal or lower than 5 as a *High* signal, and any rank above 5 as a *Low* signal.

The main focus of the regression above is the coefficient c on the triple interaction term. The coefficient measures whether investors' willingness to rank stocks *High* following good returns (an increase in R_{jt}) is larger for growth stocks ($I(Growth_{jt} = 1)$), and more so in periods leading up to overvaluation ($I(Overval_t) = 1$). To allow for a clear interpretation of the results, the regression also contains all main effects and interaction terms. Moreover, the regression includes firm fixed effects to remove investors' time-invariant propensity to rank a given stock *High* as opposed to *Low* and contest fixed effects.[35] Inference is based on double clustering by time and contest.[36]

Table 9 presents the results of the analysis. In Panel A, we focus on growth stocks. Column (1) shows the results from a simple regression of investors' propensity to buy a stock on the stock's past returns. Like DHJ and our own analysis in Table 8, we confirm that investors' propensity to rank *High* rises with the stock's return over the previous week. In Column (2) we investigate whether over-extrapolation rises leading up to market-wide overvaluation. We find that this is indeed the case. Column (3) provides some evidence that, over the full sample, the propensity to rank a stock *High* following good returns is higher for growth stocks than for all other stocks. Column (4) estimates the full specification of Eq.(32). The coefficient on the triple interaction term is significant at the 1% level. Thus, the table provides strong evidence that the propensity to rank stocks *High* based on extrapolation is particularly high for growth stocks and leading up to overvaluation. In Panel B of Table 9, we repeat the analysis for value stocks. As reported previously, the extrapolative behavior among value stocks tends to be weaker than for other stocks in the cross section. Furthermore, the extrapolation of value stocks' returns is further reduced leading up to overvaluation. Overall, these results show that return extrapolation leading up to overvaluation is stronger for growth stocks and, therefore, could potentially explain the stronger value premium observed after overvaluation.

The limitations in the Forcerank sample do not allow us to extend the analysis to market-wide undervaluation states due to the short sample period. To further examine the behavior of extrapolative beliefs about value and growth stocks leading up to both market-wide misvaluation

[35] Introducing the contest fixed effects is effectively equivalent to controlling for industry-time fixed effects in the regression since all contests in our sample are weekly, and the vast majority of contests are industry-based.

[36] We have also experimented with other clustering choices and fixed effects and obtained similar results.

states, in the next section we use analysts' price targets from I/B/E/S as an alternative longer-running source of data on beliefs.

4.3.3 Extrapolative Beliefs in the Cross Section: Analyst Price Target Revisions

Oftentimes, sell-side equity analysts provide one-year ahead target prices for the stocks they cover. To the extent that analyst price targets reveal the beliefs of sophisticated investors, it could be informative to examine the expectations of a different set of investors relative to the ones represented in the Forcerank database.[37]

We collect consensus price targets from I/B/E/S at the end of each quarter Q from 1999 to 2018. One would calculate implied returns from these prices to measure analyst expectations. This approach, however, has its drawbacks. The implied return will have the past stock price in the denominator, which is also included in the calculation of past returns. Therefore, to avoid a potential mechanical correlation between analyst expectations computed as implied returns and past stock returns, we use a different measure of analyst expectations. We argue that price target revisions will provide a more accurate metric in measuring analysts' beliefs about future stock market returns. We calculate price target revisions as the percentage difference between two consecutive price targets that span one quarter to capture the change in analysts' expectations about future stock returns. Using Fama-MacBeth regressions, we regress the cross section of price target revisions in quarter Q on lagged quarterly returns over quarters $Q-1$,...,$Q-4$ as follows:

$$Rev_{iQ} = a + \sum_{k=1}^{4} b_k * R_{iQ-k} + \sum_{k=1}^{4} c_k * R_{iQ-k} * I(V) + \sum_{k=1}^{4} d_k * R_{iQ-k} * I(G) + \epsilon_{iQ}, \tag{33}$$

where Rev_{iQ} stands for revisions in analysts consensus price targets over quarter Q, R_{iQ-1},...,R_{iQ-4} are stocks' lagged returns over quarters $Q-1$,..., $Q-4$, $I(V)$ is a dummy variable equal to one for stocks classified as value at portfolio formation (defined as the top 30% of stocks in terms of book-to-market ratios), and $I(G)$ is a dummy variable equal to one for stocks classified as growth at portfolio formation (defined as the bottom 30% of stocks in terms of book-to-market ratios).[38] The goal of this regression is to examine whether analysts' expectations are extrapolative and more so for value and growth stocks leading up to extreme misvaluation states. To this end, we run the Fama-MacBeth regressions in the six months prior to different market-wide valuation states (overvaluation, normal, and undervaluation).

Table 10 presents the results for the Fama-MacBeth regressions described above. Across all columns, the evidence suggests that price target revisions are positively related to past stock returns,

[37] The limitation of this sample is that not all firms have analyst coverage and the sample of firms that are covered by analysts is likely to contain larger, more profitable firms with better information environments (Lang and Lundholm (1996)). Furthermore, price targets could suffer from an upward bias (Brav and Lehavy (2003)) and other biases due to analysts' career concerns and investment banking relations. Nevertheless, to the extent that analyst price target revisions reflect expectations of future stock returns, the analyses in this section can shed further light on the return extrapolation channel.

[38] Our results are qualitatively similar when using deciles or quintiles to define value and growth stocks. We use top/bottom 30% of B/M as the cutoff metric for value/growth to ensure better coverage of value and growth stocks in the I/B/E/S sample.

with a larger sensitivity of revisions to more recent returns relative to more distant returns. Column (2) shows that, leading up to market-wide overvaluation, analysts increase their price targets more for growth stocks than for value stocks after observing good returns over the four previous quarters. In contrast, Column (6) shows that, leading up to market-wide undervaluation, analysts lower their price targets more for value stocks than for growth stocks after observing poor returns over the four previous quarters. Leading up to normal market-wide valuation states, the extrapolative behavior of price target revisions does not seem to differ across value, growth, and all other stocks. Overall, these results are in line with the dynamics of beliefs in the cross section that are embedded in our model and provide support for (over)extrapolation as a mechanism behind the value premium.

4.3.4 Buying/Selling of Value and Growth Stocks Leading up to Misvaluation

As our final set of tests in support of the return-extrapolation channel, we examine whether investors' buying and selling demand for value and growth stocks leading up to market-wide misvaluation are positively correlated with past return realizations for these stocks. If so, we would expect that, leading up to market-wide overvaluation, the buying demand for growth stocks to be more highly correlated with past returns than it is for other stocks. In contrast, leading up to market-wide undervaluation, the selling demand for value stocks should be more highly correlated with past returns than it is for other stocks.

Following Chordia, Roll, and Subrahmanyam (2002, 2005, 2008), buys and sells for individual stocks are classified based on tick-level data using the Lee and Ready (1991) algorithm.[39] For each stock, signed order imbalance (i.e., net buying) is calculated as dollar buys minus dollar sells divided by buys plus sells. This measure is available every month, and we average it over each quarter Q. Using Fama-MacBeth regressions, we regress average order imbalance in quarter Q, OIB_{iQ}, on lagged quarterly returns over quarters $Q-1$ to $Q-4$ as follows:

$$OIB_{iQ} = a + \sum_{k=1}^{4} b_k * R_{iQ-k} + \sum_{k=1}^{4} c_k * R_{iQ-k} * I(V) + \sum_{k=1}^{4} d_k * R_{iQ-k} * I(G) + \epsilon_{iQ}, \tag{34}$$

where $I(V)$ ($I(G)$) is a dummy variable equal to one for stocks classified as value (growth) at portfolio formation. The sample period is from 1993 to 2013. Our goal is to examine whether there are differences in net buying pressure for value and growth stocks leading up to extreme misvaluation states. To this end, we run the Fama-MacBeth regressions in the six months prior to different market-wide valuation states (overvaluation, normal, and undervaluation). The value and growth dummy variables ($I(V)$, $I(G)$) let us detect significant differences in net buying pressure for stocks that become value or growth leading up to market-wide misvaluation.

Table 11 presents the results for the Fama-MacBeth regressions described above. Columns (1), (3), and (5) show that net buying pressure is positively related to past returns over the previous four quarters, and this holds for all states of market-wide valuation. The combined dependence of order imbalance on past returns (i.e., the sum of the coefficients b_1, b_2, b_3, and b_4) is larger

[39]We thank Tarun Chordia for providing the data on order imbalance for the cross section of stocks.

leading up to market-wide overvaluation and undervaluation than in the run-up to normal market valuation. Column (2) shows that, leading up to market-wide overvaluation, the dependence of demand pressure on past returns is higher for growth stocks than for value and all other stocks. Since growth stocks have a positive order imbalance (i.e., buying pressure) leading up to overvaluation, this result implies that investors increase their net buying of growth stocks more so than for other stocks after observing positive returns over the previous four quarters. In contrast, Column (6) shows that, leading up to market-wide undervaluation, the positive relation between demand pressure and past returns is higher for value stocks than for growth and all other stocks. In unreported results, we show that value stocks have a negative order imbalance (i.e., selling pressure) leading up to undervaluation. Therefore, the coefficients in Column (6) suggest that investors increase their net selling of value stocks more so than other stocks after observing negative returns over the previous four quarters. Leading up to normal market-wide valuation states, the positive dependence of demand pressure on past returns is higher for growth stocks, but the effect is smaller than in the periods leading up to overvaluation.[40]

Overall, the evidence in Table 11 is consistent with the idea that investors (over)extrapolate past stock returns in general, and in particular, they extrapolate the good returns of growth stocks leading up to market-wide overvaluation and the poor returns of value stocks in the run-up to undervaluation. This leads to the misvaluation of these stocks and their eventual return reversal, thus creating the value premium.

5 Alternative Explanations

The results presented in the previous section support the main mechanism of our model, i.e., return extrapolation. In this section, we test whether two alternative mechanisms can help explain the conditionality of the value premium on market-wide misvaluation. We first examine whether our empirical evidence is consistent with fundamental extrapolation, which is based on the idea that investors extrapolate past fundamentals (e.g., cash-flows) when forecasting future fundamentals. Next, we study an explanation based on a risk story, namely, the conditional CAPM.

5.1 Fundamental Extrapolation

A number of papers in behavioral finance use extrapolation of fundamentals (e.g., dividends, earnings, cash flows) to explain empirical findings like the equity premium, momentum, long-run reversal, the value premium, and return bubbles.[41] An implication from this literature is that fundamental extrapolation leads to overvaluation and subsequent return reversal.[42] We examine in more

[40]The extrapolative behavior of buying and selling activity for value and growth stocks that we document is consistent with Giglio et al (2021) who show that investor beliefs are reflected in portfolio allocations.

[41]See Barberis, Shleifer, and Vishny (1998), Fuster, Laibson, and Mendel (2010), Choi and Mertens (2019), Alti and Tetlock (2014), Hirshleifer, Li, and Yu (2015), and Bordalo et al (2020), among others. See Barberis (2018) for a review of the literature on fundamental extrapolation.

[42]The empirical evidence for fundamental extrapolation appears to be mixed. Lakonishok, Shleifer, and Vishny (1994) show that extrapolation of sales growth leads to overvaluation, especially for growth firms. Daniel and Titman

detail whether expectations about the fundamentals of value and growth stocks are extrapolative and whether their behavior changes leading up to market-wide misvaluation.

We use revisions in analysts' consensus earnings forecasts as our proxy for changes in beliefs about future fundamentals. Using Fama-MacBeth regression, each quarter, we regress forecast revisions on the growth rate of EPS over the previous four quarters. The Fama-MacBeth regressions are run in the six months prior to different market-wide valuation states. Further details about the empirical setup are provided in the Appendix. Table A1 in the Appendix shows that forecast revisions are extrapolative with respect to past earnings growth rates. However, we do not find strong evidence that the extrapolative behavior of forecast revisions is stronger for growth stocks leading up to overvaluation or stronger for value stocks in the run-up to undervaluation. Therefore, to the extent that EPS forecast revisions capture beliefs about future fundamentals, we find that fundamental extrapolation is not likely to be the driving force behind the conditional behavior of the value premium.

We also examine whether fundamental extrapolation plays a role in investors' buying and selling decisions about value and growth stocks leading up to market-wide misvaluation. We perform an analysis similar to the one in Section 4.3.4, where we also include past changes in fundamentals in regression (34). More specifically, we include percentage growth in return on equity, $RoeG$, for quarters $Q-1$ to $Q-4$ both as individual terms and as interactive terms with the dummy variables $I(V)$ and $I(G)$. Further details are provided in the Appendix. Table A2 in the Appendix shows that buying and selling decisions are still mainly driven by past returns in the presence of past fundamentals. Growth in Roe in more distant quarters (i.e., $Q-3$ and $Q-4$) is a significant predictor of future buying/selling demand, but the effect is much smaller compared to past returns. We do not find strong evidence that the extent to which buying (selling) demand depends on past fundamentals is stronger for growth (value) stocks leading up to overvaluation (undervaluation). However, controlling for past fundamentals, the relation between buying (selling) demand for growth (value) stocks and past returns is stronger in the run-up to overvaluation (undervaluation).

In summary, while we find some suggestive evidence that investors extrapolate past fundamentals, this type of extrapolation is not likely to capture the strong dependence of the value premium on the state of market-wide misvaluation.

5.2 Time-Varying Market Beta of Value and Growth Stocks

The results so far indicate that return extrapolation is a plausible behavioral driver of the value premium, and it helps reconcile why such a premium is concentrated in states of severe market misvaluation. However, states in which the market is extremely over- or undervalued may be correlated with good or bad macroeconomic conditions, and previous research has documented that the market betas of value and growth stocks are different, depending on the state of the economy (Petkova and Zhang (2005)). To examine whether the profitability of the value premium

(2006) find that fundamental extrapolation exists among intangible fundamentals but not tangible ones. Recently, Bordalo et al (2019) show that the return spread based on analyst expectations is significant in the cross section of stocks. However, this result only holds for equally-weighted portfolios.

following severe market-wide misvaluation periods is driven by differences in risk between value and growth stocks, we compute the market betas of value and growth stocks in these periods.

Specifically, we estimate the market betas of value and growth portfolios using 126-day rolling market model regressions with daily data.[43] Table A3 in the Appendix reports the betas of value and growth portfolios conditional on RMV. Following periods of overvaluation, growth stocks have higher betas than value stocks and, following periods of undervaluation, value stocks have higher betas than growth stocks. Higher betas for growth stocks following periods of overvaluation during which such stocks perform poorly is inconsistent with a risk-based explanation. Higher betas for value stocks following market-wide undervaluation support a risk story. However, the differences in betas between value and growth stocks are not high enough to explain the value premium observed in these periods. For example, for the 90% cutoff, the beta spread is 0.62, whereas the corresponding value premium is 2.8% per month during the post-portfolio formation year. For beta to account for the value premium in these states, the market risk premium would have to be 4.52% per month (54.20% per year), which is not plausible.

Table A3 in the Appendix reports the alphas of the value-minus-growth strategy in different states of RMV. The results show that the alphas are statistically significant for all specifications corresponding to an overvalued or undervalued market. Following normal market-wide valuation, the alpha of the value-minus-growth strategy is negative. However, its economic magnitude is relatively small. Overall, the evidence in Table A3 reveals that the spread in betas between value and growth stocks following different states of RMV is not large enough to explain the magnitude of the value premium following periods of misvaluation. It is unlikely that our previous results are driven by differences in market exposure between value and growth stocks.

6 Robustness Tests

In this section, we perform several additional tests to examine the robustness of the main results. Specifically, we use earnings-to-price (E/P) and cash flow-to-price (CF/P) as alternative valuation ratios to B/M, and we use value-weighted portfolio returns. We also examine a different measure of market-wide misvaluation.

When we replace B/M with E/P and CF/P and perform our main analysis in Table IA2 in the Internet Appendix, the results are consistent with our previous results using B/M, in that the value premium is large and significant only after periods of market-wide over- or undervaluation.

The main results of the paper are also reproduced for value-weighted portfolio returns in Tables IA3 and IA4 of the Internet Appendix. A notable result in Table IA3 is that the value-weighted value premium one month and one year after portfolio formation is not statistically significant following states of normal market-wide valuation. This suggests that the unconditional value-weighted premium recorded in the literature comes entirely from states of market-wide misvaluation.

[43] We use ten lags of the market return in estimating market betas every day, using a regression specification of the form $r_{i,t} = \beta_0 r_{m,t} + \beta_1 r_{m,t-1} + ... + \beta_{10} r_{m,t-10} + \epsilon_{i,t}$. The sum of the estimated coefficients $\hat{\beta}_0 + \hat{\beta}_1 + ... + \hat{\beta}_{10}$ is our measure of beta every day. Monthly beta is defined as the average of daily betas within a month.

Table IA3 shows that the value-weighted value premium is large and significant only following periods of market-wide over- or undervaluation. The regression analysis of Table IA4 shows that market-wide misvaluation is a strong predictor of the value-weighted value premium after controlling for a host of other variables.

Turning to our RMV metric for market-wide misvaluation, we note that it is an intuitive measure of market-wide valuation that relies on the mean of the cross-sectional distribution of B/M ratios. To account for higher moments of the cross-sectional B/M distribution, we use an alternative measure to capture periods with significant market-wide misvaluation. This alternative measure quantifies the distance between the entire cross-sectional distribution of firm-level B/M ratios over the portfolio-formation period and the panel distribution of firm-level B/M ratios over the long-run historical period using the Mann-Whitney U test. Further details about the construction of this measure, denoted RMV^{mwz}, are in the Internet Appendix.

We replicate the analysis in Tables 2 and 5, using RMV^{mwz} based on B/M as a measure of market-wide misvaluation. The results are presented in Tables IA5 and IA6 of the Internet Appendix. These results show that our previous conclusions hold when using an alternative measure to identify states of market-wide under- or overvaluation.

7 Conclusion

In this paper, we develop a stylized model of financial markets that links time-series variation in the value premium to return extrapolation. The intuition of our model is that return extrapolation at the aggregate market level and within the cross section of equities interact to produce a large and significant value premium. On the one hand, when extrapolators move capital into the equity market following stocks' good recent performance, they push the market price even higher, eventually leading to market overvaluation. Their allocation to equities is not symmetric across all assets but heavily directed towards the better-performing stocks within the equity market. These stocks become relatively more overvalued compared to stocks that have lower or negative past performance. In a typical value strategy, such stocks will be classified as growth stocks at portfolio formation. The subsequent correction of the overvaluation of these assets results in the cross-sectional value premium. On the other hand, when extrapolators leave the equity market following a poor recent performance, they disproportionately sell the relatively poor-performing stocks. Such stocks are likely to populate the value portfolio in a typical value strategy. The subsequent correction of their undervaluation results in the cross-sectional value premium.

The main implication of our model is that the value premium is stronger following periods of extreme market-wide misvaluation. Further, our model implies that the cross-sectional value premium largely stems from the overvaluation of growth stocks in good times and the undervaluation of value stocks in bad times. The empirical results in the paper are consistent with these model predictions. Using the deviation of the aggregate B/M ratio from its historical benchmark as a measure of market-wide misvaluation, we show that the profitability of the value premium is large and significant following periods of market-wide misvaluation. The value premium either does not exist or is very low following periods of normal valuation.

We provide further evidence that, around periods of market-wide misvaluation, the pattern of investor demand for equities is consistent with the framework of our model. In particular, we show that equity funds experience inflows (outflows) leading up to significant market-wide overvaluation (undervaluation).

We also present evidence consistent with the argument that return (over)extrapolation is a possible behavioral mechanism behind our results. Using a survey-based proxy for investors' expectations about the future market return, we show that following states of extreme market-wide misvaluation that also coincide with extremely optimistic (pessimistic) expectations, the value premium is mainly driven by the price correction of growth (value) stocks. We provide further support for the extrapolation channel by (i) investigating extrapolative beliefs in the cross section using survey data from an online crowdsourcing platform, (ii) measuring return expectations based on analyst price target revisions, and (iii) investigating the dependence of buying and selling pressure for value and growth stocks on past returns in the run-up to different market-wide misvaluation states. We also consider two alternative mechanisms as potential explanations for our findings and show that neither fundamental extrapolation nor a risk explanation based on time-varying market betas is sufficient to explain our empirical evidence.

Finally, we show that time-variation in the value premium conditional on market-wide misvaluation provides quantifiable benefits for investors. In particular, a strategy that implements a value-minus-growth strategy following periods of market-wide misvaluation and holds the market portfolio (or T-bills) otherwise results in a higher mean return and lower volatility than the unconditional value-minus-growth strategy.

Our paper contributes to the understanding of the value premium by examining the impact that extrapolative capital flows in and out of the stock market have on cross-sectional return predictability. The evidence we provide suggests that the value premium is related to return extrapolation and errors in investor expectations.

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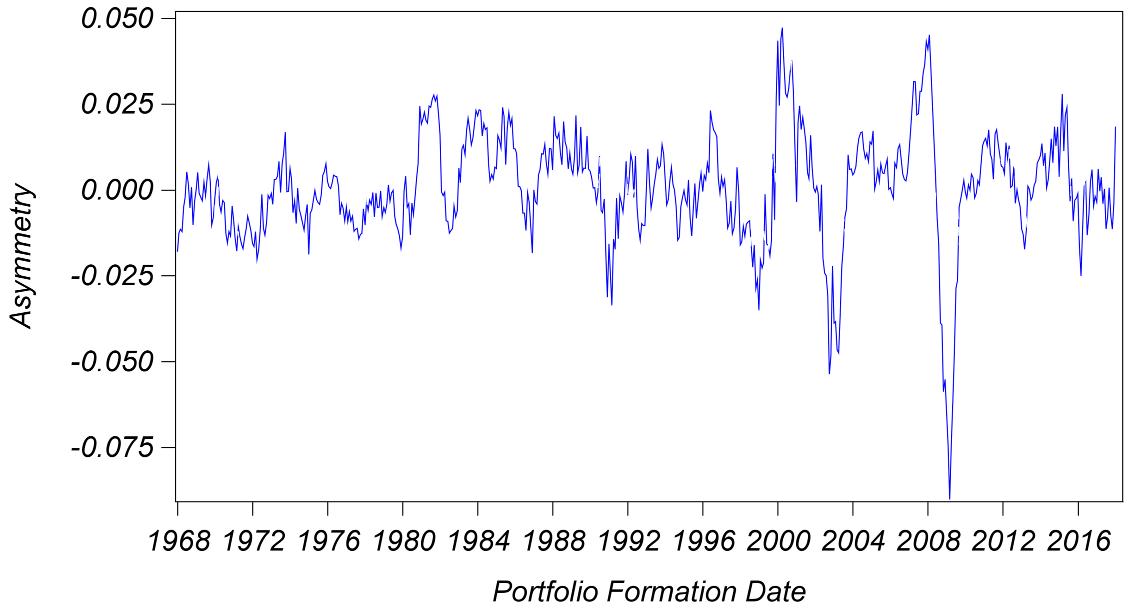
Panel A



Panel B

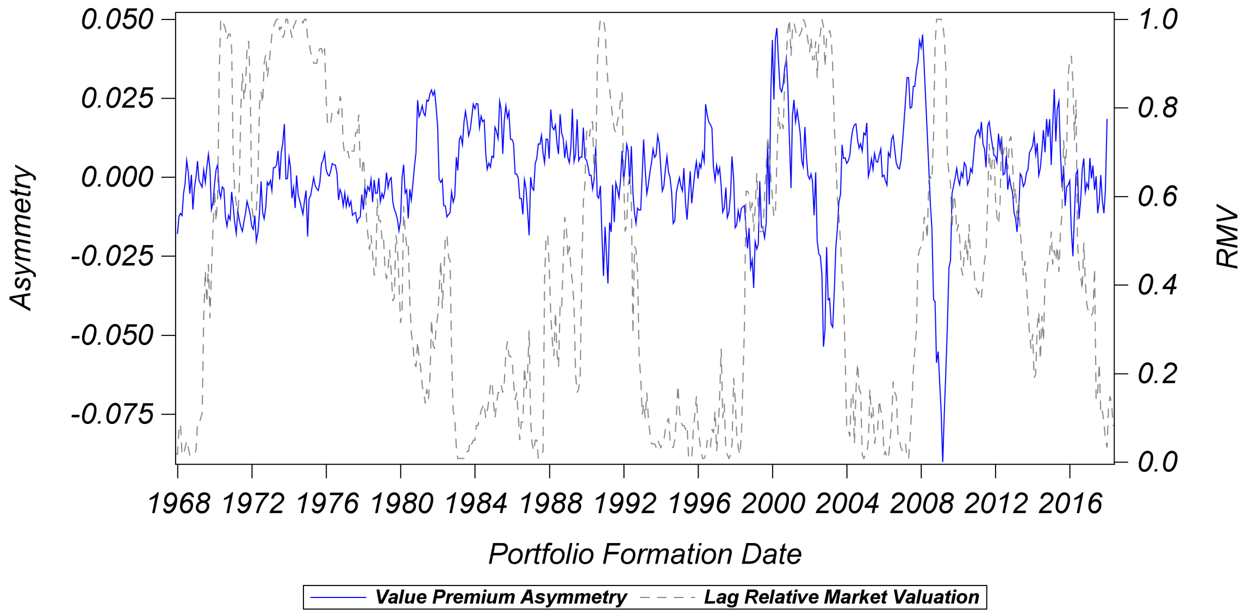


Figure 1
Asymmetric Contribution of Value and Growth to the Value Premium
We sort stocks into deciles based on their book-to-market ratios. In each portfolio formation month t, we estimate the Value Premium Asymmetry (VPA) as the contribution of growth stocks' underperformance relative to value stocks' overperformance to the subsequent 12-month value premium. We define VPA as $ln(\frac{R_{\text{D5mD1}}}{R_{\text{D10mD5}}})$. R_{D5mD1} is the gross return of the mid book-to-market decile minus the return of growth stocks, while R_{D10mD5} is the gross return of value stocks minus the return of stocks in the mid book-to-market decile. When $VPA = 0$, value and growth stocks contribute equally to the value premium. When $VPA > 0$, the value premium is driven mainly by the underperformance of growth stocks after portfolio formation, and when $VPA < 0$ the value premium is driven by the overperformance of value stocks after portfolio formation. The dotted plot in Panel B (right y-axis) represents the lagged values of relative market valuation, RMV, which measures market-wide valuation relative to the historical benchmark.

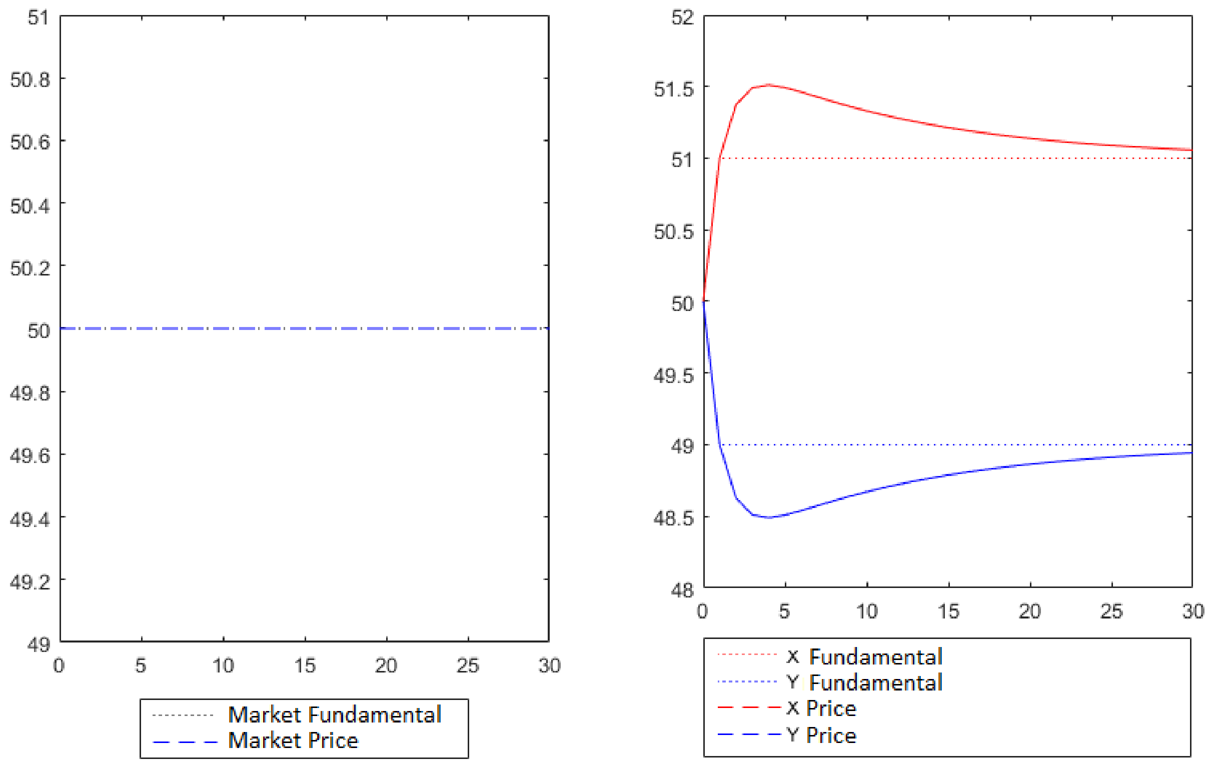
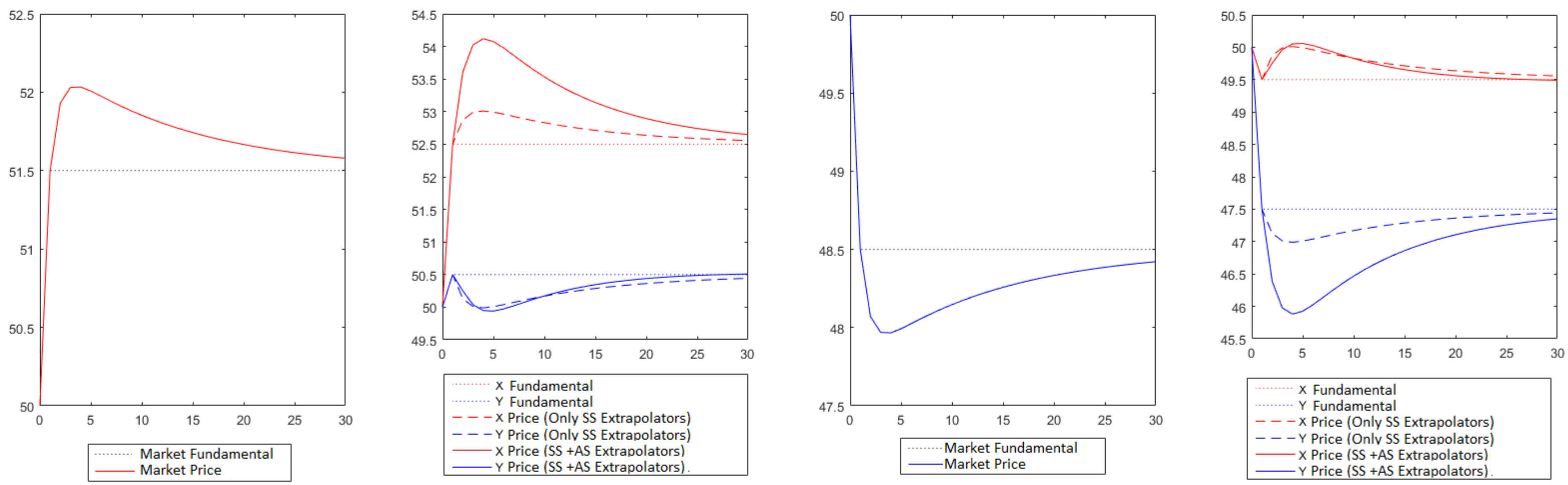


Figure 2
Model: Price Dynamics in Normal Market States
The figure plots the evolution of risky assets' prices after a zero-net aggregate cash-flow shock at time $t = 1$. The left graph shows the dynamic of aggregate market-wide prices, while the right graph documents the price behavior of stocks in groups X and Y. While the market as a whole experiences a zero shock, the difference between the cash-flow shocks for stocks in X and Y is set to be positive, i.e., stocks in X receive a positive fundamental shock, while stocks in Y receive a negative shock of the same magnitude. Each graph uses a continuous-line format to show the behavior of cross-sectional asset prices in the presence of extrapolators. In each panel, we also report the counterfactual behavior that asset prices would display in the absence of extrapolators in the market (referred to as "Fundamental"). Further details on the simulation used to generate these graphs are in Section 2.



Panel A

Panel B

Figure 3
Model: Price Dynamics in Overvalued and Undervalued Market States
The figure plots the evolution of risky assets' prices after either a positive market-wide cash-flow shock (Panel A) or after a negative market-wide cash-flow shock (Panel B) at time $t = 1$. The left graph of each panel documents price dynamics at the aggregate level, while the right graph documents the price behavior of stocks in groups X and Y. In both panels, the difference between the cash-flow shocks for stocks in X and Y is positive, i.e., stocks in group X receive a better fundamental shock (a larger positive shock in Panel A or a smaller negative shock in Panel B) than stocks in group Y. Each graph uses a continuous-line format to show the behavior of cross-sectional asset prices in the presence of extrapolators. In each panel, we also report the counterfactual behavior that asset prices would display in the absence of extrapolators in the market (referred to as "Fundamental"). When documenting cross-sectional asset-price dynamics, we distinguish between asset-price dynamics when only within-equity (SS) extrapolators exist in the market (long dashed line) as opposed to when both within-equity and asset-class extrapolators (AS) participate in the market. Further details on the simulation used to generate these graphs are in Section 2.

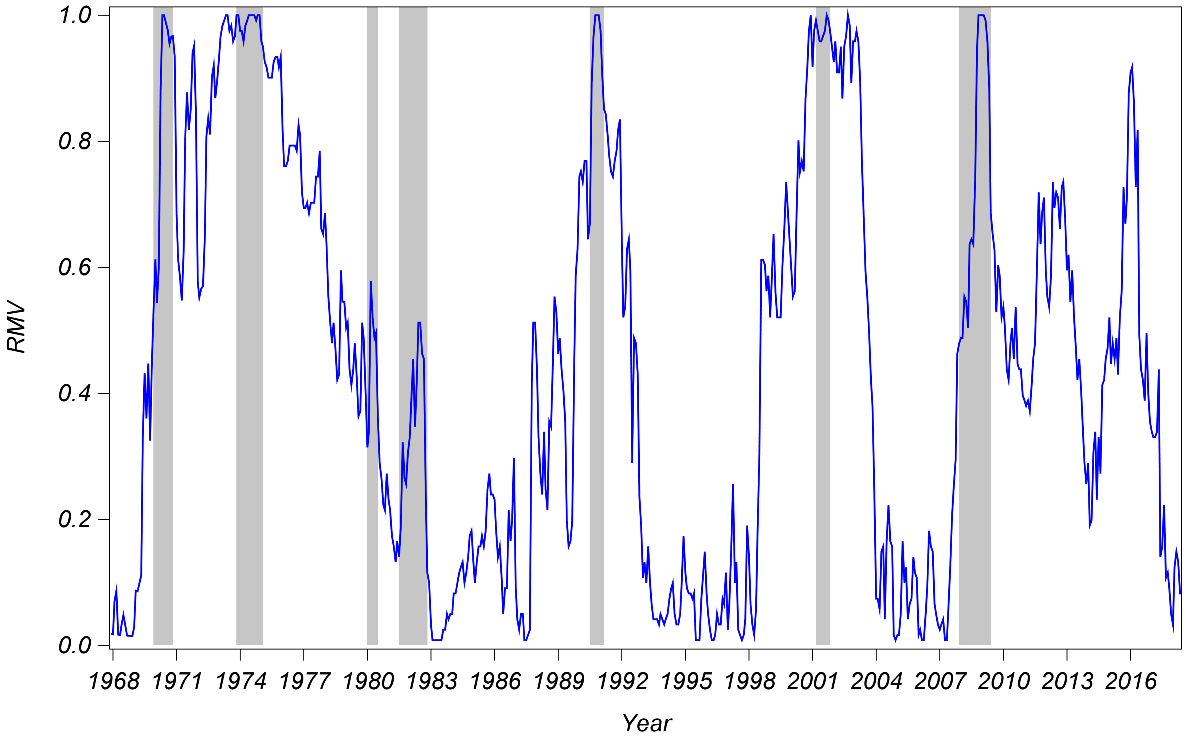


Figure 4
Time Series of Relative Market Valuation, RMV

This figure plots the time series of relative market valuation, RMV, together with NBER recessions (shaded areas), for 1968-2018. To calculate RMV, we first compute the market-wide B/M ratio as the cross-sectional average of individual stocks' B/M ratios. Then, for each month t, we obtain the past 10 years of the time series of market-wide B/M ratios from $t-120$ to $t-1$. We then find the percentile standing of the market-wide B/M ratio at time t in the historical distribution of market-wide B/M ratios over the last 10 years. We refer to this measure as relative market-wide valuation, denoted as RMV. The values of RMV are in the interval (0,1), and they are inversely related to the state of market-wide valuation, i.e., large (small) RMV corresponds to market-wide undervaluation (overvaluation). For example, if $RMV = 0.5$ ($RMV = 0.95$) then the current market-wide B/M is in the bottom 5% (top 95%) of the historical benchmark distribution and, therefore, this is a period of market-wide overvaluation (undervaluation).

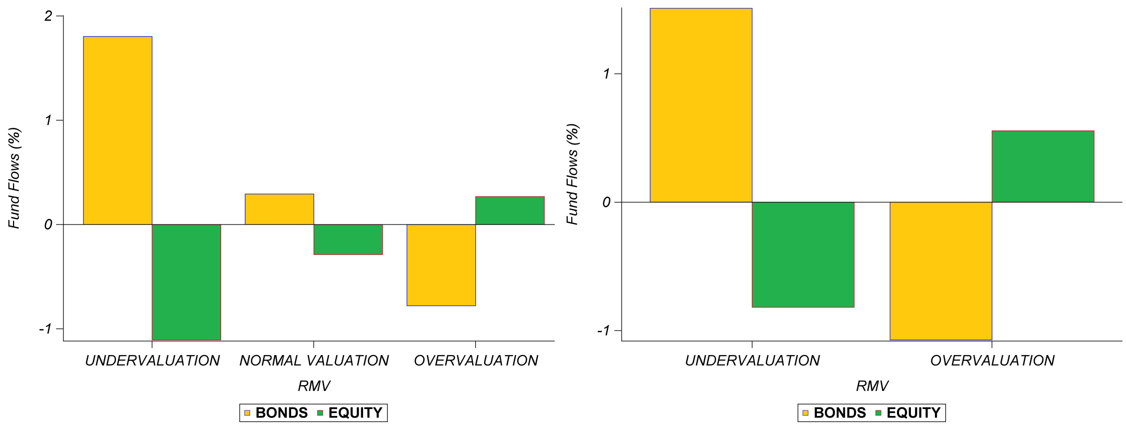


Figure 5
Flows to Bond and Equity Funds Leading up to Market-Wide Misvaluation
This figure presents flows to domestic equity and bond mutual funds in the run-up to different market-wide valuation states. Flows are defined as the ratio of dollar flows (the sum of "new sales" minus "redemption" plus "exchanges in" minus "exchanges out") and lagged total net asset value (TNA). Domestic equity flows are aggregated over growth, aggressive growth, income&growth, income equity, and sector funds. Bond flows are aggregated over corporate bonds, global bonds, high yield bonds, MBS, national municipal bonds, state municipal bonds, and stratified income bonds. The left side of the figure reports flows leading up to undervaluation (RMV above 0.75), normal valuation (RMV between 0.25 and 0.75), and overvaluation (RMV below 0.25). The right side of the panel reports flows leading up to undervaluation and overvaluation, relative to the flows observed in the run-up to normal valuation states. The sample period is 2000-2018.

Table 1
Model Simulation for Value Premium under Different Levels of Market-Wide Misvaluation

This table reports simulated results for the value premium under different levels of market-wide misvaluation. *Market condition* indicates whether the market is overvalued, normal, or undervalued. Group X consists of stocks with positive cash-flow news, while group Y consists of stocks with negative cash-flow news. *Shock to X* and *Shock to Y* show the cash-flow shocks to groups X and Y in different scenarios. *Shock to market* is the average of *Shock to X* and *Shock to Y*. If *Shock to market*$= 0$, then we define this scenario as *Normal*. If *Shock to market*> 0, then we define that case as *Overvalued*. If *Shock to market*< 0, then we define that case as *Undervalued*. *X price deviation* (*Y price deviation*) is the maximum of the absolute difference between price and fundamental value for X (Y). *X return (%)* is calculated as $\frac{P_{X,T}-P_{X,t}}{P_{X,t}}$, where t is the time when X's price reaches its peak, and T is the terminal date. *Y return (%)* is calculated as $\frac{P_{Y,T}-P_{Y,t}}{P_{Y,t}}$, where t is the time when Y's price reaches its bottom, and T is the terminal date. *Premium (%)* is the difference between *Y return (%)* and *X return (%)*.

Market condition	Shock to market	Shock to X	Shock to Y	X price deviation	Y price deviation	X return (%)	Y return (%)	Premium (%)
Overvalued	1.5	2.5	0.5	1.19	0.04	-1.95	0.09	2.04
Overvalued	1.0	2.0	0.0	0.99	0.21	-1.66	0.42	2.09
Overvalued	0.5	1.5	-0.5	0.80	0.41	-1.36	0.77	2.13
Normal	0.0	1.0	-1.0	0.30	0.30	-0.50	0.52	1.02
Undervalued	-0.5	0.5	-1.5	0.41	0.80	-0.74	1.50	2.24
Undervalued	-1.0	0.0	-2.0	0.21	0.99	-0.42	1.87	2.29
Undervalued	-1.5	-0.5	-2.5	0.04	1.19	-0.09	2.26	2.35

Table 2

Market-Wide Misvaluation and the Value Premium

This table reports monthly equal-weighted returns (in %) for value stocks (V), growth stocks (G), and the value premium (VmG) under different scenarios of market-wide misvaluation. At the end of each month, we sort stocks listed on NYSE, NASDAQ, and AMEX by B/M. The top decile is defined as value stocks, while the bottom decile is defined as growth stocks. We identify 7 market-wide valuation states based on the level of RMV. For each valuation state, we report the number of months (N) under different valuation scenarios, the market-wide B/M (the cross-sectional average of individual stock B/M ratios), the value spread, the average monthly return of portfolios V, G, and VmG over the next 1 month and the next 12 months. Under *Stock-level Misvaluation* we report the breakpoint ranking of value and growth stocks' valuations relative to the historical pooled cross-sectional distribution of firm-level B/M ratios. Newey-West t-statistics are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1968-2018.

				Stock-level Misvaluation		1 month			12 months		
condition	N	Market B/M	Value spread	V	G	V	G	VmG	V	G	VmG
Overvalued ($RMV_{0.05}$)	85	0.54	2.05	0.737	0.106	1.22**	-1.02	2.24***	0.58*	-0.71**	1.29***
						[2.21]	[-1.67]	[5.97]	[1.72]	[-2.36]	[3.47]
Overvalued ($RMV_{0.10}$)	129	0.55	2.07	0.730	0.104	1.22***	-0.48	1.70***	0.94***	-0.28	1.22***
						[2.62]	[-0.82]	[4.30]	[2.74]	[-0.92]	[4.05]
Overvalued ($RMV_{0.20}$)	195	0.59	2.06	0.735	0.109	1.31***	-0.18	1.49***	1.03***	-0.09	1.12***
						[3.78]	[-0.42]	[5.02]	[3.65]	[-0.36]	[4.50]
Normal (RMV_{normal})	285	0.79	2.12	0.812	0.132	1.36***	1.37***	-0.01	1.56***	0.96***	0.60***
						[3.03]	[3.25]	[-0.03]	[4.40]	[2.87]	[2.64]
Undervalued ($RMV_{0.80}$)	120	1.18	2.41	0.928	0.153	2.94***	0.02	2.91***	3.31***	0.75	2.56***
						[2.83]	[0.03]	[4.19]	[3.74]	[1.18]	[4.92]
Undervalued ($RMV_{0.90}$)	91	1.26	2.43	0.938	0.163	3.47***	0.05	3.42***	3.63***	0.83	2.80***
						[2.93]	[0.05]	[4.15]	[3.59]	[1.14]	[4.80]
Undervalued ($RMV_{0.95}$)	67	1.29	2.44	0.943	0.167	3.95**	0.66	3.29***	3.96***	0.97	2.99***
						[2.52]	[0.69]	[2.88]	[3.18]	[1.10]	[4.16]

Table 3
Market-Wide Misvaluation and Decile Portfolio Returns

This table reports the average returns (in %) for 12 months after portfolio formation for ten decile B/M portfolios following different market-wide misvaluation scenarios. The average return of the value strategy (VmG) is also reported. At the end of each month, we calculate firm-level B/M and sort stocks listed in NYSE, NASDAQ, and AMEX into decile portfolios. The top decile represents value stocks (V), while the bottom decile represents growth stocks (G). We report the number of months under different scenarios of RMV. Newey-West t-statistics are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1968-2018.

condition	N	V (D10)	D9	D8	D7	D6	D5	D4	D3	D2	G (D1)	VmG (D10-D1)
Overvalued ($RMV_{0.05}$)	85	0.58*	0.57**	0.51*	0.48**	0.36	0.24	0.19	0.03	-0.16	-0.71**	1.29***
		[1.72]	[2.11]	[1.90]	[1.96]	[1.40]	[1.03]	[0.78]	[0.13]	[-0.68]	[-2.36]	[3.47]
Overvalued ($RMV_{0.10}$)	129	0.94***	0.85***	0.77***	0.73***	0.63**	0.55**	0.47*	0.37	0.21	-0.28	1.22***
		[2.74]	[3.05]	[2.83]	[2.83]	[2.48]	[2.21]	[1.94]	[1.46]	[0.84]	[-0.92]	[4.05]
Overvalued ($RMV_{0.20}$)	195	1.03***	0.94***	0.88***	0.83***	0.76***	0.72***	0.64***	0.53**	0.39*	-0.09	1.12***
		[3.65]	[4.05]	[3.85]	[3.78]	[3.50]	[3.27]	[3.02]	[2.49]	[1.76]	[-0.36]	[4.50]
Normal (RMV_{normal})	285	1.56***	1.50***	1.42***	1.36***	1.36***	1.35***	1.35***	1.29***	1.16***	0.96***	0.60***
		[4.40]	[5.03]	[5.24]	[5.06]	[5.01]	[5.06]	[4.86]	[4.66]	[4.02]	[2.87]	[2.64]
Undervalued ($RMV_{0.80}$)	120	3.31***	2.40***	2.11***	1.91***	1.70***	1.52***	1.45**	1.23**	1.07*	0.75	2.56***
		[3.74]	[3.71]	[3.51]	[3.32]	[3.11]	[2.80]	[2.53]	[2.10]	[1.88]	[1.18]	[4.92]
Undervalued ($RMV_{0.90}$)	91	3.63***	2.66***	2.34***	2.14***	1.88***	1.69***	1.62***	1.40**	1.21*	0.83	2.80***
		[3.59]	[3.66]	[3.48]	[3.32]	[3.10]	[2.80]	[2.59]	[2.16]	[1.89]	[1.14]	[4.80]
Undervalued ($RMV_{0.95}$)	67	3.96***	2.85***	2.50***	2.31***	1.99***	1.82***	1.74**	1.54**	1.36*	0.97	2.99***
		[3.18]	[3.26]	[3.17]	[3.10]	[2.87]	[2.60]	[2.39]	[2.03]	[1.77]	[1.10]	[4.16]

Table 4
Market-Wide Misvaluation and the Value Premium: Jensen's Alpha

This table reports monthly alphas (in %) for value stocks (V), growth stocks (G), and the value premium (VmG) following different scenarios of market-wide misvaluation. At the end of each month, we sort stocks listed on NYSE, NASDAQ, and AMEX by B/M. The top decile is defined as value stocks, while the bottom decile is defined as growth stocks. We identify 7 market-wide valuation states based on the level of RMV. For each valuation state, we report the number of months (N) under different valuation scenarios, the next month Jensen's alphas, and the next 12-month Jensen's alphas of V, G, and VmG. Newey-West t-statistics are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1968-2018.

		1 month			12 months		
Market condition	N	V	G	VmG	V	G	VmG
Overvalued ($RMV_{0.05}$)	85	1.52***	-0.68**	2.20***	0.42***	-0.94***	1.36***
		[4.04]	[-2.13]	[6.08]	[2.88]	[-7.62]	[7.89]
Overvalued ($RMV_{0.10}$)	129	1.10***	-0.62**	1.72***	0.42***	-0.79***	1.21***
		[3.09]	[-2.03]	[4.60]	[3.79]	[-8.26]	[9.09]
Overvalued ($RMV_{0.20}$)	195	0.76**	-0.80***	1.56***	0.34***	-0.73***	1.07***
		[2.50]	[-3.11]	[5.44]	[3.83]	[-10.79]	[10.50]
Normal (RMV_{normal})	285	0.46	0.35	0.10	0.75***	0.21**	0.54***
		[1.48]	[1.32]	[0.33]	[7.45]	[2.46]	[5.11]
Undervalued ($RMV_{0.80}$)	120	2.90***	-0.02	2.92***	2.76***	0.17**	2.59***
		[4.05]	[-0.08]	[4.17]	[13.42]	[2.10]	[11.26]
Undervalued ($RMV_{0.90}$)	91	3.24***	-0.20	3.45***	3.18***	0.19**	2.98***
		[4.12]	[-0.89]	[4.21]	[13.58]	[2.22]	[10.98]
Undervalued ($RMV_{0.95}$)	67	3.57***	0.23	3.34***	3.40***	0.35***	3.05***
		[3.12]	[1.12]	[2.93]	[11.92]	[3.51]	[9.05]

Table 5
Market-Wide Misvaluation and Predictability of the Value Premium

This table reports coefficient estimates of the following monthly time-series regression:

$$Value\,premium_{t,t+h} = a_0 + a_1 * DOM_t + a_2 * Value\,spread_t + a_3 * X_t + \epsilon_{t,t+h}.$$

The dependent variable is the equal-weighted h-month cumulative return of the value-minus-growth strategy, where h=3,6,12 months. DOM is defined as $(RMV - 0.5)^2$. $Value\,spread$ is the difference between the log B/M of Deciles 5 and 1, sorted by B/M after controlling for size. The control variables in X include the Sentiment Index of Baker and Wurgler (2006), the NBER recession dummy, the equal-weighted average of individual B/M ratios, the lagged risk-free rate, term spread, default spread, the aggregate dividend yield, and market volatility. Market volatility is the volatility of daily equal-weighted returns over the previous 3 months. Newey-West t-statistics are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1968-2018.

Coefficient	h=3			h=6			h=12		
$a0$	-0.19	-5.40**	-8.03***	-0.07	-5.06***	-7.54***	0.34*	-4.59***	-7.11***
	[-0.63]	[-2.44]	[-3.22]	[-0.30]	[-2.89]	[-3.98]	[1.87]	[-4.24]	[-5.86]
$a1$	12.89***	11.64***	11.93***	11.09***	9.89***	10.27***	7.58***	6.40***	6.38***
	[4.78]	[4.66]	[5.32]	[4.81]	[4.69]	[5.79]	[4.68]	[4.48]	[5.54]
$a2$		2.48**	1.56		2.37***	1.24		2.34***	1.86***
		[2.34]	[1.47]		[2.86]	[1.55]		[4.58]	[3.59]
Adj. R^2	0.10	0.14	0.26	0.14	0.21	0.44	0.13	0.27	0.53
Controls	N	N	Y	N	N	Y	N	N	Y

Table 6
Earnings Surprises Leading up to Market-Wide Misvaluation

This table reports average standardized unexpected earnings (SUE) for Value (V), Growth (G), and Decile 5 (D5) portfolios based on a sort on B/M. The average SUE for each portfolio is measured prior to different states of market-wide misvaluation. We identify 7 market-wide valuation states based on the level of RMV. For each valuation state, we report average SUE for stocks in the value and growth portfolios 12 months prior to portfolio formation. Portfolio SUE is measured as the median SUE of stocks within the portfolio. We follow Bernard and Thomas (1989) and define SUE as the difference between actual and forecasted earnings scaled by the standard deviation of unexpected earnings, estimated over the previous 20 quarters. Forecasted earnings are based on median analysts' forecasts from I/B/E/S. Newey-West t-statistics are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1988-2018.

condition	V	D5	G
Overvalued ($RMV_{0.05}$)	-0.07	0.11***	0.17***
	[-1.52]	[3.85]	[3.96]
Overvalued ($RMV_{0.10}$)	-0.08**	0.11***	0.18***
	[-2.13]	[4.69]	[4.57]
Overvalued ($RMV_{0.20}$)	-0.08***	0.10***	0.16***
	[-2.67]	[5.49]	[5.11]
Normal (RMV_{normal})	-0.11***	0.06***	0.09***
	[-4.06]	[3.78]	[3.76]
Undervalued ($RMV_{0.80}$)	-0.16***	0.01	0.05
	[-3.51]	[0.78]	[1.37]
Undervalued ($RMV_{0.90}$)	-0.17***	-0.00	0.05
	[-3.59]	[-0.10]	[1.12]
Undervalued ($RMV_{0.95}$)	-0.18***	-0.01	0.05
	[-3.48]	[-0.26]	[1.05]

Table 7
Returns Around Market-Wide Misvaluation

This table reports monthly equal-weighted returns (in %) for value stocks (V) and growth stocks (G) prior to different states of market-wide misvaluation. We identify 3 market-wide valuation states based on the level of RMV and $EXPX$. For each valuation state, we report the average monthly returns for value and growth stocks 12 months prior to portfolio formation, 1 month after portfolio formation, and 12 months after portfolio formation. Newey-West t-statistics are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1968-2018.

condition	V	G
	Panel A: Leading up to Market-wide Misvaluation	
Overvalued ($RMV_{0.20}$, $EXPX_{high}$))	-0.58	5.56***
	[-1.18]	[3.38]
Normal (RMV_{normal})	-1.35***	4.07***
	[-2.75]	[3.27]
Undervalued ($RMV_{0.80}$, $EXPX_{low}$)	-4.63***	1.23**
	[-3.08]	[2.21]
	Panel B: 1 month after Market-wide Misvaluation	
Overvalued ($RMV_{0.20}$, $EXPX_{high}$))	1.13	-0.78
	[1.53]	[-0.96]
Normal (RMV_{normal})	1.36***	1.37***
	[3.03]	[3.25]
Undervalued ($RMV_{0.80}$, $EXPX_{low}$)	3.51**	-0.06
	[2.16]	[-0.06]
	Panel C: 12 months after Market-wide Misvaluation	
Overvalued ($RMV_{0.20}$, $EXPX_{high}$))	0.96***	-0.75**
	[3.22]	[-2.02]
Normal (RMV_{normal})	1.56***	0.96***
	[4.40]	[2.87]
Undervalued ($RMV_{0.80}$, $EXPX_{low}$)	4.31***	1.31*
	[3.86]	[1.83]

Table 8
Extrapolative Expectations for Value and Growth Stocks: Survey-Based Evidence using Forcerank

Using data on investor expectations from Forcerank, we estimate a model of extrapolative expectations in the cross section of stocks:

$$CE_{it} = \gamma_0 + \sum_{s=0}^{11} \beta_s * R_{i[t-s-1,t-s]} + \epsilon_{it},$$

where CE_{it} is the consensus expectation of the week-ahead return of stock i at time t, and $R_{i[t-s-1,t-s]}$ is the return on stock i in the s weeks prior. The analysis is performed both over the full sample period 2016:02-2018:02 (Panel A), and in the 6-month period leading up to market-wide overvaluation (i.e., $RMV < 0.20$). We estimate the regression over the entire cross section of stocks available in Forcerank (Column *All*), as well as the subset of value stocks (Column *Value*) and growth stocks (Column *Growth*). Value and growth stocks are defined based on the 30^{th} and 70^{th} percentile of the B/M distribution of all stocks. The bottom of each panel reports the sum of β_s for the most recent four weeks (Month t), the two previous months (Month $t-1$ and Month $t-2$), and the entire period (*Total*). Heteroskedasticity-robust t-statistics are in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Full sample			Leading up to Market Overvaluation		
Stocks	All	Value	Growth	All	Value	Growth
R_1	3.414***	2.962***	3.927***	3.933***	2.577***	5.423***
	[14.76]	[5.56]	[9.18]	[12.54]	[3.86]	[9.35]
R_2	1.131***	0.895	1.137***	1.277***	1.151	1.591***
	[4.94]	[1.34]	[2.89]	[3.90]	[1.31]	[2.89]
R_3	1.085***	1.826***	1.198***	1.36***	0.875	2.355***
	[4.88]	[2.82]	[3.04]	[4.23]	[1.13]	[4.29]
R_4	0.856***	0.802	1.078***	1.077***	1.054	1.729***
	[3.85]	[1.38]	[2.66]	[3.43]	[1.47]	[3.00]
R_5	0.936***	0.135	1.671***	1.062***	-0.139	2.245***
	[4.31]	[0.26]	[4.43]	[3.38]	[-0.19]	[4.07]
R_6	0.889***	0.487	0.984***	1.154***	1.035	1.106*
	[4.06]	[0.92]	[2.68]	[3.49]	[1.19]	[1.90]
R_7	0.290	-0.020	0.183	0.57*	1.574*	0.744
	[1.36]	[-0.04]	[0.49]	[1.76]	[1.87]	[1.33]
R_8	0.878***	1.031*	0.800**	1.596***	1.992**	1.176**
	[4.07]	[1.89]	[2.16]	[4.77]	[2.19]	[2.04]
R_9	0.608***	0.635	0.439	1.099***	0.896	0.984*
	[2.93]	[1.38]	[1.22]	[3.57]	[1.35]	[1.81]
R_{10}	0.421**	0.292	0.690*	1.192***	0.675	1.780***
	[1.98]	[0.52]	[1.94]	[3.93]	[0.93]	[3.34]
R_{11}	0.655***	1.442***	0.622*	1.29***	2.131***	1.473***
	[3.25]	[2.94]	[1.87]	[4.10]	[2.92]	[2.71]
R_{12}	0.642***	0.550	0.880**	1.082***	0.707	1.155**
	[3.16]	[1.10]	[2.49]	[3.39]	[1.01]	[2.01]
N	15316	1448	6236	9590	900	3876
R^2	0.023	0.035	0.026	0.030	0.037	0.042
sum of β_s						
Month t	6.486	6.485	7.340	7.647	5.657	11.098
Month $t-1$	2.993	1.633	3.638	4.382	4.462	5.271
Month $t-2$	2.326	2.919	2.631	4.663	4.409	5.392
Total	11.805	11.037	13.609	16.692	14.528	21.761

Table 9
Time-varying Extrapolative Demand for Value and Growth Stocks: Survey-Based Evidence using Forcerank

We estimate a model of investor recommendations to buy stocks as a function of stock type, states of market-wide valuation (proxied by RMV), and past stock returns:

$$\begin{aligned} I(High)_{ijst} = {} & c * R_{jt} * I(Stock\_Type_{jt}) * I(Overval_t) \times R_{jt} \\ & + b_1 * R_{jt} + b_2 * I(Stock\_Type_{jt}) + b_3 * I(Overval_t) + d_1 * R_{jt} * I(Stock\_Type_{jt}) \\ & + d_2 * R_{jt} * I(Overval_t) + d_3 * I(Stock\_Type_{jt}) * I(Overval_t) + \alpha_j + \alpha_s + \epsilon_{ijst}, \end{aligned}$$

where i indexes Forcerank forecasters, j indexes a given stock, s indexes a given contest, and t indexes time. The left-hand side variable *I(High)* is a dummy variable that takes a value of 1 when the forecaster assigns a rank of 1 to 5 to the stock within a given Forcerank contest, i.e., the forecaster places the stock in the top of the distribution of future stock returns. Conversely, *I(High)* is equal to zero when the forecaster ranks a stock between 6 and 10, thus indicating the stock is likely to underperform the other stocks in the contest. $I(Stock\_Type_{jt})$ is a dummy variable equal to one for growth stocks in Panel A (bottom 30% of cross-sectional B/M distribution), and equal to one for value stocks in Panel B (top 30% of cross-sectional B/M distribution). $I(Overval_t)$ is a dummy variable equal to 1 for forecasts that are issued in the 6 months prior to an overvaluation month (a month in which RMV<0.20). R_{jt} is the return of the stock in the week in which the forecaster submits a prediction to Forcerank. Regressions include firm and contest fixed effects. The t-statistics, in brackets, are based on double clustering by time and contest. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2016:02-2018:02.

Panel A: Growth	(1)	(2)	(3)	(4)
R_{jt}	0.641***	0.537***	0.602***	0.582***
	[14.58]	[9.67]	[10.76]	[6.93]
$I(Overval)$		0.01***		0.007
		[3.04]		[0.97]
$I(Growth)$			0.031***	0.026***
			[5.47]	[3.77]
R_{jt}*$I(Overval)$		0.214***		0.036
		[2.62]		[0.32]
R_{jt}*$I(Growth)$			0.104*	-0.068
			[1.67]	[-0.79]
$I(Growth)$*$I(Overval)$				0.009
				[1.39]
R_{jt}*$I(Growth)$*$I(Overval)$				0.362***
				[3.19]
R^2	0.058	0.058	0.056	0.057
N	259,284	259,284	200,949	200,949

Panel B: Value	(1)	(2)	(3)	(4)
R_{jt}	0.641***	0.537***	0.657***	0.533***
	[14.58]	[9.67]	[12.31]	[8.12]
$I(Overval)$		0.010***		0.008
		[3.04]		[1.40]
$I(Value)$			-0.019	-0.028**
			[-1.58]	[-2.21]
R_{jt}*$I(Overval)$		0.214***		0.265***
		[2.62]		[2.68]
R_{jt}*$I(Value)$			-0.11	0.118
			[-1.24]	[1.01]
$I(Value)$*$I(Overval)$				0.018**
				[2.07]
R_{jt}*$I(Value)$*$I(Overval)$				-0.421***
				[-2.61]
R^2	0.058	0.058	0.056	0.056
N	259,284	259,284	200,949	200,949

Table 10
Extrapolative Expectations for Value and Growth Stocks: Evidence based on Analyst Price Target Revisions

The table presents the results of Fama-MacBeth regressions of the form:

$$Rev_{iQ} = a + \sum_{k=1}^{4} b_k * R_{iQ-k} + \sum_{k=1}^{4} c_k * R_{iQ-k} * I(V) + \sum_{k=1}^{4} d_k * R_{iQ-k} * I(G) + \epsilon_{iQ}$$

where Rev_{iQ} stands for revisions in analysts consensus target prices over quarter Q, R_{iQ-1},...,R_{iQ-4} are stocks' lagged returns over quarters $Q-1$,...,$Q-4$, $I(V)$ is a dummy variable equal to one for value stocks (defined as the top 30% of stocks in terms of book-to-market ratios), and $I(G)$ is a dummy variable equal to one for growth stocks (defined as the bottom 30% of stocks in terms of book-to-market ratios). The sample includes stocks with prices greater than one dollar. The Fama-MacBeth regressions are performed in the six months prior to different market-wide valuation states. The three states of market-wide valuation are Overvaluation defined as $RMV_{0.20}$, Normal defined as RMV_{normal}, and Undervaluation defined as $RMV_{0.80}$. Newey-West t-statistics are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1999-2018.

Variable	Overvaluation		Normal		Undervaluation	
	(1)	(2)	(3)	(4)	(5)	(6)
R_{iQ-1}	0.255***	0.198***	0.219***	0.211***	0.237***	0.214***
	[14.29]	[5.62]	[16.21]	[10.19]	[16.19]	[11.58]
R_{iQ-2}	0.043***	0.021**	0.022***	0.012*	0.084***	0.056***
	[4.69]	[2.35]	[4.05]	[1.87]	[4.97]	[3.58]
R_{iQ-3}	0.001	-0.013	-0.016***	-0.024***	0.043***	0.014***
	[0.25]	[-1.55]	[-3.38]	[-3.77]	[3.72]	[3.49]
R_{iQ-4}	-0.056***	-0.054***	-0.019***	-0.023***	0.017***	-0.004
	[-3.67]	[-3.80]	[-3.04]	[-2.76]	[3.27]	[-0.90]
$R_{iQ-1} * I(V)$		0.006***		0.007		0.019**
		[3.97]		[0.83]		[2.14]
$R_{iQ-2} * I(V)$		-0.021		0.013		0.040***
		[-0.92]		[1.34]		[3.48]
$R_{iQ-3} * I(V)$		0.020*		0.019***		0.036***
		[1.86]		[2.95]		[3.98]
$R_{iQ-4} * I(V)$		-0.015		0.005		0.011
		[-0.74]		[0.45]		[1.57]
$R_{iQ-1} * I(G)$		0.077***		-0.005		0.015*
		[3.29]		[-0.47]		[1.89]
$R_{iQ-2} * I(G)$		0.055***		-0.005		0.036***
		[3.78]		[-0.71]		[3.46]
$R_{iQ-3} * I(G)$		0.007		-0.013		0.032***
		[0.64]		[-1.53]		[3.75]
$R_{iQ-4} * I(G)$		0.001		-0.006		0.029***
		[0.10]		[-0.57]		[3.71]
N	360	360	693	693	264	264

Table 11
Buying/Selling Behavior for Value and Growth Stocks: Evidence based on Order Imbalance

The table presents the results of Fama-MacBeth regressions of the form:

$$OIB_{iQ} = a + \sum_{k=1}^{4} b_k * R_{iQ-k} + \sum_{k=1}^{4} c_k * R_{iQ-k} * I(V) + \sum_{k=1}^{4} d_k * R_{iQ-k} * I(G) + \epsilon_{iQ}$$

where OIB_{iQ} stands for average order imbalance (in dollars) over quarter Q, $R_{iQ-1}...R_{iQ-2}$ are stocks' lagged returns over quarters $Q-1...Q-4$, $I(V)$ is a dummy variable equal to one for value stocks, and $I(G)$ is a dummy variable equal to one for growth stocks. The sample includes stocks with prices greater than one dollar. The Fama-MacBeth regressions are performed in the six months prior to different market-wide valuation states. The three states of market-wide valuation are Overvaluation defined as $RMV_{0.20}$, Normal defined as RMV_{normal}, and Undervaluation defined as $RMV_{0.80}$. Newey-West t-statistics are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1993-2013.

Variable	Overvaluation		Normal		Undervaluation	
	(1)	(2)	(3)	(4)	(5)	(6)
R_{Q-1}	0.027***	0.017***	0.012***	0.007***	0.007**	-0.003
	[4.94]	[3.36]	[10.43]	[3.48]	[2.29]	[-1.15]
R_{Q-2}	0.032***	0.022***	0.019***	0.012***	0.016***	0.007***
	[5.66]	[4.25]	[4.93]	[3.79]	[3.36]	[2.67]
R_{Q-3}	0.033***	0.024***	0.015***	0.012***	0.022***	0.013***
	[6.27]	[4.96]	[3.42]	[2.74]	[2.92]	[2.84]
R_{Q-4}	0.031***	0.025***	0.015***	0.013***	0.033***	0.023***
	[5.92]	[4.73]	[3.36]	[3.14]	[3.94]	[3.12]
$R_{Q-1} * I(V)$		-0.002		-0.003		0.016***
		[-0.27]		[-1.44]		[2.73]
$R_{Q-2} * I(V)$		0.001		0.003		0.033***
		[0.24]		[1.17]		[3.89]
$R_{Q-3} * I(V)$		0.007		0.000		0.022***
		[1.30]		[0.21]		[3.91]
$R_{Q-4} * I(V)$		-0.006		-0.006**		0.029***
		[-1.29]		[-2.15]		[3.68]
$R_{Q-1} * I(G)$		0.046***		0.012**		0.010**
		[5.04]		[2.40]		[2.18]
$R_{Q-2} * I(G)$		0.029***		0.010**		0.012***
		[2.94]		[2.29]		[3.29]
$R_{Q-3} * I(G)$		0.029***		0.008**		0.024***
		[3.35]		[2.18]		[3.69]
$R_{Q-4} * I(G)$		0.031***		0.011**		0.025***
		[3.48]		[2.41]		[2.92]
N	452	452	528	528	205	205

APPENDIX

A1. Fundamental Extrapolation

Forecast Revisions

We obtain analyst consensus forecasts and EPS data from I/B/E/S. Forecast revisions are calculated as the percentage difference between forecasts that span one quarter to capture the change in analysts' expectations about future earnings. Using Fama-MacBeth regressions, we regress forecast revisions over quarter Q on percentage growth in EPS over the previous four quarters as follows:

$$EPSRev_{iQ} = a + \sum_{k=1}^{4} b_k * EPSG_{iQ-k} + \sum_{k=1}^{4} c_k * EPSG_{iQ-k} * I(V) + \sum_{k=1}^{4} d_k * EPSG_{iQ-k} * I(G) + \epsilon_{iQ}, \tag{A1}$$

where $EPSRev_{iQ}$ stands for revisions in analysts consensus forecasts over quarter Q, $EPSG_{iQ-1}$,..., $EPSG_{iQ-4}$ are stocks' EPS growth rates for quarters $Q-1$,...,$Q-4$, and $I(V)$ ($I(G)$) is a dummy variable equal to one for value (growth) stocks. Due to data availability, we define value (growth) stocks as the top (bottom) 30% of stocks in terms of book-to-market ratios. The sample includes stocks with prices greater than one dollar. To examine whether analysts' earnings expectations are extrapolative and more so for value and growth stocks leading up to extreme misvaluation states, we run the Fama-MacBeth regressions in the six months prior to different market-wide valuation states.

Table A1 presents the results for the Fama-MacBeth regressions described above. Across Columns (1), (3), and (5), the evidence suggests that forecast revisions are significantly positively related to EPS growth rates over the previous two quarters. Column (2) shows that, leading up to market-wide overvaluation, the propensity of analysts to revise their forecasts in the direction of EPS growth rates over the previous quarter is higher for both value and growth stocks than for other stocks. Column (6) shows that, leading up to market-wide undervaluation, analysts have a higher propensity to revise their price targets in the direction of EPS growth over quarter $Q-3$ for growth stocks. Overall the results in Table A1 suggest that analysts tend to extrapolate past earnings growth. However, this behavior is not more pronounced for growth (value) stocks leading up to overvaluation (undervaluation). Therefore, extrapolative beliefs about earnings growth are not likely to explain the conditional behavior of the value premium with respect to market-wide misvaluation.

Buying/Selling Demand

For each stock, we obtain signed order imbalance (i.e., net buying) as dollar buys minus dollar sells divided by buys plus sells.[44] We average this monthly measure over each quarter Q. We also obtain

[44]Following Chordia, Roll, and Subrahmanyam (2002, 2005, 2008), buys and sells for individual stocks are classified based on tick-level data using the Lee and Ready (1991) algorithm.

monthly return on equity, *Roe*, for each stock and construct the growth rate of this variable over a quarter, *RoeG*. Using Fama-MacBeth regressions, we regress average order imbalance in quarter Q, OIB_{iQ}, on lagged quarterly returns and lagged growth in *Roe* over quarters $Q-1$ to $Q-4$ as follows:

$$OIB_{iQ} = a + \sum_{k=1}^{4} b_k * R_{iQ-k} + \sum_{k=1}^{4} c_k * RoeG_{iQ-k} + \sum_{k=1}^{4} d_k * R_{iQ-k} * I(V) + \sum_{k=1}^{4} e_k * R_{iQ-k} * I(G) + \sum_{k=1}^{4} f_k * RoeG_{iQ-k} * I(V) + \sum_{k=1}^{4} h_k * RoeG_{iQ-k} * I(G) + \epsilon_{iQ} \tag{A2}$$

where $I(V)$ ($I(G)$) is a dummy variable equal to one for stocks classified as value (growth) at portfolio formation. Our goal is to examine whether there are differences in net buying pressure for value and growth stocks leading up to extreme misvaluation states. Therefore, we run the Fama-MacBeth regressions in the six months prior to different market-wide valuation states (overvaluation, normal, and undervaluation). The value and growth dummy variables ($I(V)$, $I(G)$) let us detect significant differences in net buying pressure for stocks that become value or growth leading up to market-wide misvaluation.

Table A2 presents the results for the Fama-MacBeth regressions described above. Across all market-wide valuation states, demand pressure is positively related to past returns over the previous four quarters (with the exception of $Q-1$ leading up to undervaluation). Growth in *Roe* in more distant quarters (i.e., $Q-3$ and $Q-4$) is a significant predictor of future demand, but the effect is much smaller compared to past returns. Leading up to market-wide overvaluation, the dependence of demand pressure on past returns is higher for growth stocks than for other stocks. In addition, the dependence of demand pressure on past *RoeG* in $Q-1$ and $Q-4$ is higher for growth stocks than for other stocks, but the effect is smaller than the one for past returns. Leading up to market-wide undervaluation, the positive relation between demand pressure and past returns is higher for value stocks than for other stocks. The dependence of demand pressure on past *RoeG* in $Q-3$ is higher for value stocks than for other stocks, but the effect is smaller than the one for past returns. Overall, Table A2 shows that buying and selling decisions are still mainly driven by past returns in the presence of past fundamentals. We do not find strong evidence that the extent to which buying (selling) demand depends on past fundamentals is stronger for growth (value) stocks leading up to overvaluation (undervaluation). Extrapolation of past fundamentals is not likely to capture the conditionality of the value premium with respect to extreme market-wide valuation.

Table A1
Extrapolative Expectations About Fundamentals: Evidence based on Analyst Forecast Revisions

The table presents the results of Fama-MacBeth regressions of the form:

$$EPSRev_{iQ} = a + \sum_{k=1}^{4} b_k * EPSG_{iQ-k} + \sum_{k=1}^{4} c_k * EPSG_{iQ-k} * I(V) + \sum_{k=1}^{4} d_k * EPSG_{iQ-k} * I(G) + \epsilon_{iQ}$$

where $EPSRev_{iQ}$ stands for revisions in analysts consensus forecasts over quarter Q, $EPSG_{iQ-1}$,...,$EPSG_{iQ-4}$ are stocks' lagged EPS growth rates for quarters $Q-1$,...,$Q-4$, $I(V)$ is a dummy variable equal to one for value stocks (defined as the top 30% of stocks in terms of book-to-market ratios), and $I(G)$ is a dummy variable equal to one for growth stocks (defined as the bottom 30% of stocks in terms of book-to-market ratios). The sample includes stocks with prices greater than one dollar. The Fama-MacBeth regressions are performed in the six months prior to different market-wide valuation states. The three states of market-wide valuation are Overvaluation defined as $RMV_{0.20}$, Normal defined as RMV_{normal}, and Undervaluation defined as $RMV_{0.80}$. Newey-West t-statistics are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1999-2018.

Variable	Overvaluation		Normal		Undervaluation	
	(1)	(2)	(3)	(4)	(5)	(6)
$EPSG_{iQ-1}$	0.014***	-0.019*	0.003**	0.003	0.029***	0.058***
	[3.29]	[-1.87]	[2.21]	[0.66]	[4.57]	[5.05]
$EPSG_{iQ-2}$	0.001	0.005**	0.001**	0.001	0.003***	0.003
	[0.46]	[2.25]	[2.04]	[1.36]	[3.76]	[1.01]
$EPSG_{iQ-3}$	-0.002***	-0.003***	-0.001	-0.002**	-0.003***	-0.004
	[-4.26]	[-4.83]	[-1.43]	[-2.05]	[-3.49]	[-1.61]
$EPSG_{iQ-4}$	0.001	0.001	0.000	0.001	0.002	0.013*
	[1.15]	[1.07]	[0.12]	[0.23]	[0.99]	[1.88]
$EPSG_{iQ-1} * I(V)$		0.049***		0.009*		-0.042***
		[4.25]		[1.86]		[-4.77]
$EPSG_{iQ-2} * I(V)$		-0.011***		-0.001		0.006*
		[-4.09]		[-1.14]		[1.85]
$EPSG_{iQ-3} * I(V)$		-0.005***		0.004**		0.003
		[-2.62]		[2.50]		[0.62]
$EPSG_{iQ-4} * I(V)$		0.004*		-0.003		-0.008
		[1.95]		[-0.52]		[-1.17]
$EPSG_{iQ-1} * I(G)$		0.043***		0.004		-0.051***
		[4.15]		[0.66]		[-4.60]
$EPSG_{iQ-2} * I(G)$		-0.008***		0.002		-0.008***
		[-3.12]		[1.23]		[-2.71]
$EPSG_{iQ-3} * I(G)$		-0.001		0.003**		0.009***
		[-0.63]		[2.05]		[3.27]
$EPSG_{iQ-4} * I(G)$		-0.001		-0.005		-0.017**
		[-0.84]		[-0.88]		[-2.24]
N	360	360	693	693	264	264

Table A2
Buying/Selling Behavior for Value/Growth Stocks: Past Returns and Fundamentals

The table presents the results of Fama-MacBeth regressions of the form:

$$OIB_{iQ} = a + \sum_{k=1}^{4} b_k * R_{iQ-k} + \sum_{k=1}^{4} c_k * RoeG_{iQ-k} + \sum_{k=1}^{4} d_k * R_{iQ-k} * I(V) + \sum_{k=1}^{4} e_k * R_{iQ-k} * I(G)$$
$$+ \sum_{k=1}^{4} f_k * RoeG_{iQ-k} * I(V) + \sum_{k=1}^{4} h_k * RoeG_{iQ-k} * I(G) + \epsilon_{iQ}$$

where OIB_{iQ} is the avreage order imabalance for stock i in quarter Q (defined as dollar buys minus dollar sells divided by buys plus sells), R_{iQ-1},...,R_{iQ-4} are stocks' lagged returns over quarters $Q-1$,...,$Q-4$, $I(V)$ ($I(G)$) is a dummy variable equal to one for stocks classified as value (growth) stocks at portfolio formation, and $RoeG_{iQ}$ stands for the percentage change in Roe for stock i over quarter Q. The Fama-MacBeth regressions are performed in the six months prior to different market-wide valuation states. The three states of market-wide valuation are Overvaluation defined as $RMV_{0.20}$, Normal defined as RMV_{normal}, and Undervaluation defined as $RMV_{0.80}$. Newey-West t-statistics are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1993-2013.

Variable	Overvaluation	Normal	Undervaluation
R_{iQ-1}	0.019***	0.006**	-0.003
	[4.50]	[2.49]	[-1.14]
R_{iQ-2}	0.023***	0.012***	0.008***
	[5.26]	[4.03]	[3.37]
R_{iQ-3}	0.025***	0.012***	0.016***
	[5.94]	[3.29]	[2.73]
R_{iQ-4}	0.025***	0.014***	0.026***
	[5.25]	[3.88]	[3.96]
$RoeG_{iQ-1}$	0.001**	0.001**	0.000
	[-2.06]	[2.10]	[-0.78]
$RoeG_{iQ-2}$	0.000	0.000	0.001***
	[-0.56]	[0.82]	[-2.76]
$RoeG_{iQ-3}$	0.000	0.001**	0.000
	[-1.13]	[2.24]	[-1.01]
$RoeG_{iQ-4}$	0.001**	0.001***	0.001***
	[1.96]	[-3.20]	[2.84]
$R_{iQ-1} * I(V)$	-0.001	-0.005*	0.012***
	[-0.19]	[-1.75]	[3.01]
$R_{iQ-2} * I(V)$	-0.001	0.003	0.032***
	[-0.16]	[0.98]	[5.18]
$R_{iQ-3} * I(V)$	0.008	-0.003	0.014**
	[1.58]	[-1.40]	[2.30]
$R_{iQ-4} * I(V)$	-0.003	-0.006***	0.018***
	[-0.54]	[-2.62]	[2.74]
$R_{iQ-1} * I(G)$	0.044***	0.011***	0.008*
	[5.33]	[3.60]	[1.80]
$R_{iQ-2} * I(G)$	0.033***	0.010***	0.014***
	[3.71]	[3.41]	[3.17]
$R_{iQ-3} * I(G)$	0.035***	0.011***	0.022***
	[4.45]	[3.90]	[3.98]
$R_{iQ-4} * I(G)$	0.031***	0.012***	0.014***
	[3.38]	[2.67]	[3.93]
$RoeG_{iQ-1} * I(V)$	-0.001**	0.001**	0.000
	[-2.12]	[2.44]	[0.95]
$RoeG_{iQ-2} * I(V)$	-0.001**	0.001***	0.000
	[-2.49]	[3.32]	[-0.34]
$RoeG_{iQ-3} * I(V)$	-0.001**	0.001***	0.000
	[-2.32]	[3.24]	[0.77]
$RoeG_{iQ-4} * I(V)$	0.000	0.001***	0.000
	[-0.31]	[3.21]	[0.14]
$RoeG_{iQ-1} * I(G)$	0.002**	-0.002***	0.000
	[2.45]	[-3.36]	[-0.02]
$RoeG_{iQ-2} * I(G)$	0.000	-0.001*	0.002
	[0.59]	[-1.92]	[1.22]
$RoeG_{iQ-3} * I(G)$	-0.001	-0.001**	0.002**
	[-1.56]	[-2.16]	[2.33]
$RoeG_{iQ-4} * I(G)$	0.002**	0.000	0.000
	[2.36]	[-0.71]	[0.01]
N	452	528	205

Table A3
Market-wide Misvaluation and Market Betas of Value and Growth Stocks

This table reports the average market betas of value and growth stocks and the difference in alpha and beta between value and growth stocks (VmG) under different scenarios of market-wide misvaluation. At the end of each month, we calculate B/M and sort stocks listed on NYSE, NASDAQ, and AMEX by B/M. The top decile is defined as value stocks, while the bottom decile is defined as growth stocks. We identify 7 market-wide valuation states based on the level of RMV. For each valuation state, we report the number of months (N) under different market-wide valuation levels, the average market betas of value stocks, growth stocks, and the difference of beta and alpha between value and growth stocks. Newey-West t-statistics are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1968-2018.

condition	N	Value Beta	Growth Beta	VmG Alpha
Overvalued ($RMV_{0.05}$)	85	0.92	1.06	1.18***
				[7.44]
Overvalued ($RMV_{0.10}$)	129	0.94	1.07	1.19***
				[9.01]
Overvalued ($RMV_{0.20}$)	195	0.96	1.10	1.08***
				[9.60]
Normal (RMV_{normal})	285	1.27	1.03	-0.29**
				[-2.05]
Undervalued ($RMV_{0.80}$)	120	1.56	0.95	1.44***
				[4.32]
Undervalued ($RMV_{0.90}$)	91	1.57	0.95	2.01***
				[5.01]
Undervalued ($RMV_{0.95}$)	67	1.57	0.94	2.47***
				[5.02]

Internet Appendix

for

"Extrapolators at the Gate: Market-wide Misvaluation and the Value Premium"

IA1. Mean Reversion in Market-wide Valuation Ratios

To examine whether market-wide valuation ratios are mean-reverting, we estimate the following partial adjustment model, following Fama and French (2000):

$$Y_{t+1} - Y_t = a_0 + a_1 * Y_t + a_2 * [Y_t - Y_{t-1}] + \epsilon_{t+1}, \tag{IA1}$$

where Y corresponds to market-wide B/M, E/P, or CF/P. The coefficient a_1 measures the rate of mean reversion. We update the denominator of each valuation ratio annually and we use annual data in the regressions. We use both equally-weighted and value-weighted ratios. The results in Table IA1 show that the equally-weighted valuation ratios have a higher rate of mean reversion than the value-weighted ratios. Furthermore, the rate of mean reversion for the equally-weighted ratios is statistically significant, while that for the value-weighted ratios is not.

IA2. Value Investing Based on Market-Wide Misvaluation

We show that the value premium is higher following market-wide over- or undervaluation. We complement that finding by examining the benefit for an investor who follows a dynamic value strategy based on market-wide misvaluation. The first strategy, referred to as DYNVALUE_1, implements value-minus-growth in a given month if RMV at the end of the previous month is either high (i.e., $RMV_{0.80}$) or low (i.e., $RMV_{0.20}$), and holds the 1-month T-bill otherwise. The second strategy, DYNVALUE_2, differs from the first one in that it holds the value-weighted market portfolio for intermediate RMV values. We quantify benefits to the investor in terms of improved mean portfolio returns, return volatility, and Campbell and Thompson (2008) utility gains.[1] To address the concern that the benefit of conditioning on RMV may be confined to certain periods, we construct the aforementioned statistics recursively.[2]

[1] As in Campbell and Thompson (2008), we consider a single-period mean-variance investor whose coefficient of relative risk aversion is equal to 3.

[2] Specifically, we construct our statistics assuming that an investor could implement DYNVALUE_1 or DYNVALUE_2 starting at any month between January 1968 to December 2007. Choosing January 1968 as the first investment-start date is based on the availability of RMV. Choosing December 2007 as the last investment-start date allows us to use 10 years of data to construct relevant out-of-sample statistics.

Figure IA1 presents the results for DYNVALUE_1 (Panel A) and DYNVALUE_2 (Panel B), respectively. In all subpanels, the date reported on the x-axis refers to the investment-start date. The left part of each panel provides a comparison between the mean returns obtained when implementing the static value strategy (dashed line) and the mean returns obtained with our RMV-based dynamic value strategy (solid line). The right part of each panel provides a similar comparison for return volatility.

For strategy DYNVALUE_1 (Panel A), with the exception of the investment-start dates between 1999 and 2003, the mean returns obtained while conditioning on RMV are approximately 20% higher than the returns obtained in the static case. When comparing return volatilities, there is a reduction in return volatility in the same order of magnitude. Therefore, an investor who trades the dynamic value strategy receives not only higher mean returns but also lower risk. Higher average returns and lower volatility translate into large utility gains for a hypothetical mean-variance investor. These results are confirmed, and in fact, strengthen, in Panel B of Figure IA1, where we repeat the analysis with our second dynamic strategy DYNVALUE_2.[3]

The benefits for an investor who trades the value strategy dynamically are also economically large. For instance, an investor endowed with \$1 in the beginning of 1968 would have accumulated \$195 by the end of 2018 executing the static value strategy. This accumulation of wealth would have grown to \$855 (\$5136) had the investor traded DYNVALUE_1 (DYNVALUE_2).

IA3. Robustness Tests

The main analysis in the paper uses the B/M ratio to classify stocks into value and growth categories and to identify states of market-wide misvaluation. We substitute B/M with two other fundamental-to-price ratios that have been used previously, E/P and CF/P, to sort stocks into value and growth and to define the market-wide misvaluation measure RMV. Firm-level earnings used in year t are total earnings before extraordinary items for the last fiscal year end in $t-1$, while cash flow used in year t is total earnings before extraordinary items, plus equity's share of depreciation, plus deferred taxes (if available) for the last fiscal year end in $t-1$. For both E/P and CF/P, the market value of equity in the denominator is updated at the end of each month. Therefore, we calculate firm-level E/P (CF/P) on a monthly basis. The aggregate market E/P (CF/P) is the average of firm-level E/P (CF/P), winsorized at 1% and 99%. We exclude firms with negative E/P (CF/P) from the analysis. Value and growth portfolios sorted on E/P (CF/P) are still equally-weighted.

Table IA2 reports the average returns of value, growth, and value-minus-growth portfolios for one and 12 months after portfolio formation, using E/P and CF/P as valuation ratios. The results in Table IA2 are consistent with our previous results using B/M. The value premium is large and significant only after periods of market-wide over- or undervaluation.

While previously we used equally-weighted value and growth portfolios, here we also study

[3] DYNVALUE_2 achieves 0.5 percentage points higher average return for every possible investment-start date, or a 50% higher average monthly return than the static value strategy. Moreover, the volatility of the dynamic value strategy is much lower than the volatility of the static strategy.

value-weighted portfolios. To save space, we report results that replicate the analysis in Tables 2 and 5 only, using value-weighted returns. The results are presented in Tables IA3 and IA4. Table IA3 shows that the value-weighted value premium is large and significant following periods of market-wide over- or undervaluation. A notable result in Table IA3 is that the value-weighted value premium one month and one year after portfolio formation is not statistically significant following states of normal market-wide valuation. This result is interesting since it suggests that the unconditional value-weighted premium recorded in the literature comes entirely from states of market-wide misvaluation.

Table IA4 shows that the predictability of DOM (as defined through RMV) for the future profitability of the value-weighted value premium remains significant. It is robust and significant in the presence of the value spread and other control variables, including the Sentiment Index of Baker and Wurgler (2006), the NBER recession dummy, the cross-sectional average of individual B/M ratios, the risk-free rate, term spread, default spread, aggregate dividend yield, and market variance.

The RMV measure is an intuitive measure of market-wide valuation. However, it does not take into account the higher moments of the cross-sectional B/M distribution. To use the full information embedded in the cross-sectional distribution of B/M, we use an alternative measure to capture periods with significant market-wide misvaluation. To the extent that the historical (panel) distribution of B/M ratios represents the long-run behavior of B/M ratios, and to the extent that stocks, on average, are given a fair valuation in the long run, we would expect that when the recent cross-sectional distribution of B/M ratios deviates significantly from the long-run benchmark distribution, there will be extreme market-wide over- or undervaluation. Following these periods, the value premium is likely to be large. To this end, we quantify the distance between the cross-sectional distribution of firm-level B/M ratios over the portfolio-formation period and the panel distribution of firm-level B/M ratios over the long-run historical period using the Mann-Whitney U test. The test produces the Mann-Whitney z-statistic for large samples, which we denote as MWZ. We use the MWZ statistic to test the null hypothesis that the current cross-sectional distribution of valuation ratios is the same as the historical benchmark. We calculate an alternative market-wide valuation measure based on the MWZ statistic, denoted as RMV^{mwz}.

Specifically, in each month t, we obtain the cross section of firm-level B/M ratios as the current distribution of valuations. We compute the historical benchmark distribution by pooling all cross-sectional distributions of B/M ratios from $t-120$ to $t-1$. We extract the centiles (from 1^{st} to 99^{th}) from the current distribution to form an approximate current distribution, and we extract the centiles from the historical benchmark distribution to form an approximate benchmark distribution. We use the two approximate distributions to conduct a Mann-Whitney U-test. Since we have large samples, the final statistics produced by the test are z-statistics. Therefore, the values of our RMV^{mwz} measure are z-statistics. When the current distribution of B/M ratios shifts significantly to the left compared to the benchmark distribution (i.e., B/M ratios become smaller, signaling market-wide overvaluation) the Mann-Whitney U-test produces a significantly negative z-statistic. For robustness, we examine three levels of significance and we denote them as $RMV_{0.01}^{mwz-}$, $RMV_{0.05}^{mwz-}$, and $RMV_{0.10}^{mwz-}$, where "-" stands for a negative z-statistic.[4] All three correspond to states of significant market-wide overvaluation. Equivalently, when the current distribution of B/M ratios shifts significantly to the right compared to the benchmark distribution (i.e., B/M ratios become larger, signaling market-wide undervaluation), the Mann-Whitney U-test produces a significantly positive z-statistic. We examine three levels of significance denoted as $RMV_{0.01}^{mwz+}$, $RMV_{0.05}^{mwz+}$, and $RMV_{0.10}^{mwz+}$, where "+" stands for a positive z-statistic. All three correspond to states of market-wide undervaluation. Finally, we define normal times as instances in which the current distribution of B/M ratios does not deviate significantly from the historical distribution and denote them as RMV_{normal}^{mwz}.

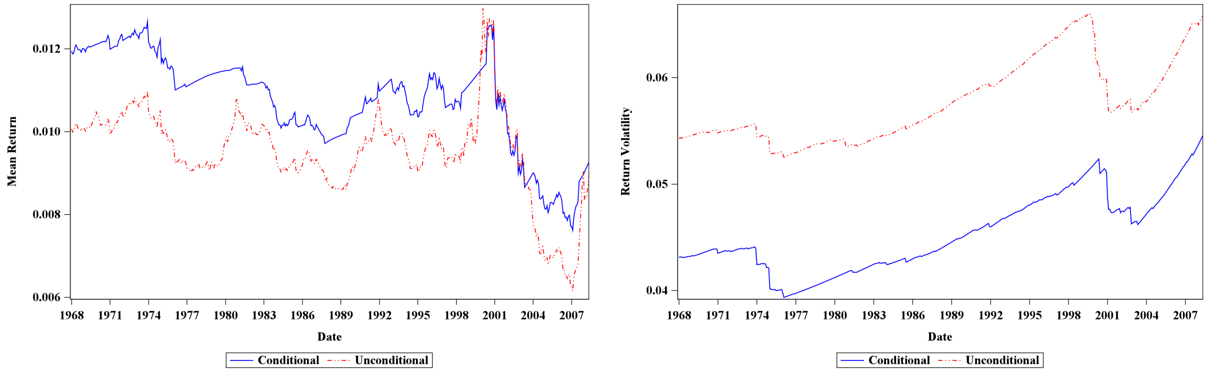
The RMV^{mwz} measure of market-wide under- or overvaluation is different from the RMV measure described earlier. The RMV^{mwz} measure is based on the entire cross-sectional distribution of B/M ratios, while RMV relies on the mean of the cross-sectional distribution alone. Therefore, if the cross-sectional distribution of B/M ratios is characterized by a difference between the mean and the median, the RMV^{mwz} measure will take that into account.[5]

To save space, we report results that replicate the analysis in Tables 2 and 5, using RMV^{mwz} based on B/M as a measure of market-wide misvaluation. The results are presented in Tables IA5 and IA6. These results show that our previous conclusions hold when using RMV^{mwz} to identify states of market under- or overvaluation.

[4] Subscripts represent the corresponding p-value of the z-statistic.

[5] RMV^{mwz} is based on a non-parametric test of whether the most recent cross-sectional distribution of B/M ratios and the historical benchmark distribution are drawn from the same population. Even though the Mann-Whitney test behind RMV^{mwz} uses all B/M observations to calculate a p-value that depends on the ranks of the observations within the distributions and thus takes into account higher moments, it is most sensitive to differences in medians between the distributions. Thus, one can view RMV^{mwz} as a non-parametric test on the difference between the medians of two distributions with higher moments also affecting the test statistic. A similar test is Kolmogorov-Smirnov, which is highly sensitive to differences in higher moments.

Panel A: Strategy DYNVALUE$_1$



Panel B: Strategy DYNVALUE$_2$

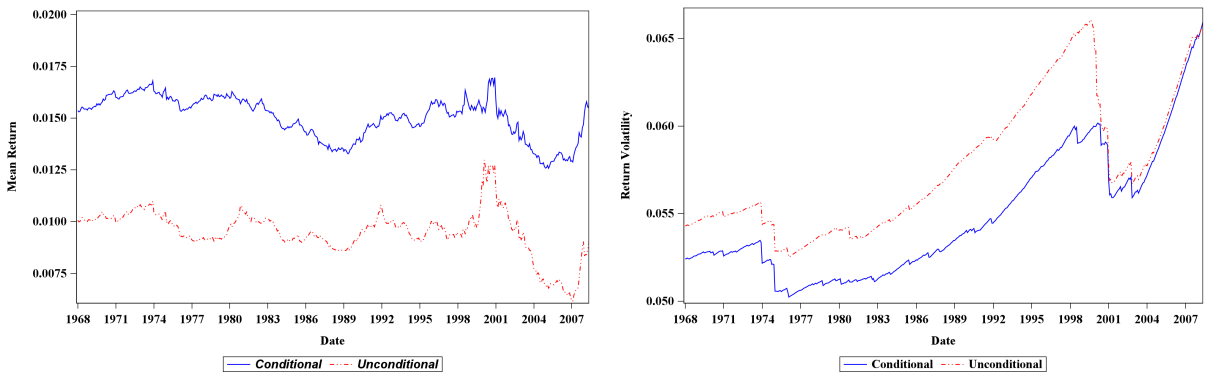


Figure IA1

Dynamic Value Strategies Conditional on Market-Wide Misvaluation

DYNVALUE$_1$ is a dynamic value strategy that implements value-minus-growth when the 1-month lagged RMV is either very high ($RMV_{0.8}$, undervaluation) or very low ($RMV_{0.2}$, overvaluation), and holds the 1-month T-bill otherwise. DYNVALUE$_2$ is a dynamic value strategy that implements value-minus-growth when the 1-month lagged RMV is either very high or very low, and holds the value-weighted market portfolio otherwise. In each graph, the date reported on the x-axis refers to the investment start date, and the statistics reported (mean and volatility) refer to an investment period that ends in December 2018. The blue solid plot reports the performance of the dynamic value strategy, while the red dashed plot shows the performance of the static value strategy.

Table IA1
Mean Reversion in Market-wide Valuation Ratios

This table reports results from the following partial adjustment model, following Fama and French (2000):

$$Y_{t+1} - Y_t = a_0 + a_1 * Y_t + a_2 * [Y_t - Y_{t-1}] + \epsilon_{t+1}.$$

The variable Y corresponds to market-wide B/M, E/P, and CF/P, respectively. The denominator of each valuation ratio is updated annually, and the regressions use annual data. Equally-weighted ratios represent the average of the cross-sectional distribution of firm-level ratios at each point in time. Value-weighted ratios are computed as the sum of firm-level fundamental variables (book value, earnings, or cash flows) divided by the sum of firm-level market value of equity at each point in time. Panel B also reports results using the CAPE measure of E/P constructed by Shiller. The t-statistics in brackets are adjusted for heteroskedasticity and serial correlation. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is from 1963 to 2018.

Panel A: Equally-weighted valuation ratios					Panel B: Value-weighted valuation ratios				
Y	a_0	a_1	a_2	$Adj.R^2$	Y	a_0	a_1	a_2	$Adj.R^2$
B/M	0.24***	-0.31***	0.08	0.11	B/M	0.02	-0.07	-0.33*	0.12
	[5.50]	[-6.51]	[0.58]			[0.84]	[-1.02]	[-1.82]	
E/P	0.02***	-0.28***	0.07	0.10	E/P	0.01	-0.15	-0.20	0.09
	[4.39]	[-5.95]	[0.42]			[1.64]	[-1.52]	[-1.38]	
CF/P	0.05***	-0.30***	0.07	0.11	CF/P	0.01	-0.10	-0.30	0.12
	[5.20]	[-6.83]	[0.48]			[1.39]	[-1.27]	[-1.56]	
					CAPE	0.00	-0.07	-0.10	0.04
						[1.19]	[-1.11]	[-0.88]	

Table IA2
Market-wide Misvaluation (calculated by E/P, CF/P) and the Value Premium (equal-weighted)

This table reports monthly equal-weighted returns (in %) of value stocks (V), growth stocks (G) and the value premium (VmG) under different market-wide misvaluation scenarios (RMV). At the end of each month, we calculate earnings-to-price (E/P) and cash flow-to-price (CF/P) and sort stocks listed in NYSE, NASDAQ and AMEX by these ratios. The top decile is defined as value stocks, while the bottom decile is defined as growth stocks. We report the number of months (N) under different scenarios of RMV, market-wide E/P or CF/P, the value spread, the average monthly return of portfolios V, G, and VmG over the next 1 month and the next 12 months. Under *Stock-level Misvaluation* we report the breakpoint ranking of value and growth stocks' valuations relative to the historical benchmark. Firm-level earnings used in year t are total earnings before extraordinary items for the last fiscal year end in $t-1$, while cash flow used in year t is total earnings before extraordinary items, plus equity's share of depreciation, plus deferred taxes (if available) for the last fiscal year end in $t-1$. For both E/P and CF/P, the market value of equity in the denominator is updated at the end of each month. Therefore, we calculate firm-level E/P (CF/P) on a monthly basis. The aggregate market E/P (CF/P) is the average of firm-level E/P (CF/P), winsorized at 1% and 99%. We exclude firms with negative E/P (CF/P) from the analysis. Value and growth portfolios sorted on E/P (CF/P) are still equally-weighted. Newey-West t-statistics are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Panel A reports results for using E/P to calculate RMV and identify value and growth stocks. Panel B reports results for using CF/P to calculate RMV and identify value and growth stocks. The sample period is 1968-2018.

Panel A. RMV calculated using E/P

				Stock-level Misvaluation		1 month			12 months		
Condition	N	Market E/P	Value spread	V	G	V	G	VmG	V	G	VmG
Overvalued ($RMV_{0.05}$)	66	0.06	1.88	0.721	0.102	0.67	-0.65	1.32***	0.34	-0.39	0.73**
						[1.04]	[-1.01]	[5.01]	[1.18]	[-0.97]	[2.31]
Overvalued ($RMV_{0.10}$)	109	0.06	1.88	0.714	0.098	0.86**	0.15	0.71***	0.52*	-0.06	0.58**
						[2.09]	[0.31]	[2.65]	[1.91]	[-0.16]	[2.52]
Overvalued ($RMV_{0.20}$)	158	0.06	1.87	0.716	0.102	1.23***	0.56	0.67***	0.77***	0.27	0.50***
						[3.56]	[1.36]	[2.71]	[2.94]	[0.92]	[2.67]
Normal (RMV_{normal})	316	0.08	1.87	0.812	0.146	0.83**	0.91**	-0.08	1.11***	1.04***	0.07
						[2.12]	[2.56]	[-0.36]	[3.60]	[3.43]	[0.42]
Undervalued ($RMV_{0.80}$)	126	0.11	2.03	0.905	0.170	3.07***	1.25	1.82***	2.76***	1.32***	1.44***
						[3.47]	[1.59]	[2.84]	[4.44]	[2.74]	[4.00]
Undervalued ($RMV_{0.90}$)	72	0.12	2.02	0.922	0.185	3.20**	0.61	2.58***	3.08***	1.14*	1.95***
						[2.52]	[0.68]	[3.46]	[3.22]	[1.79]	[3.75]
Undervalued ($RMV_{0.95}$)	46	0.13	1.97	0.926	0.185	4.06**	1.12	2.95***	3.51**	1.40*	2.11***
						[2.19]	[0.93]	[2.76]	[2.51]	[1.69]	[2.68]

Table IA2 (Continued)

Panel B. RMV calculated using CF/P

Condition	N	Market E/P	Value spread	Stock-level Misvaluation		1 month			12 months		
				V	G	V	G	VmG	V	G	VmG
Overvalued ($RMV_{0.05}$)	79	0.13	2.25	0.843	0.128	1.06**	-0.48	1.54***	0.37	-0.40	0.77**
						[1.96]	[-0.72]	[4.46]	[1.16]	[-1.34]	[2.47]
Overvalued ($RMV_{0.10}$)	121	0.13	2.24	0.840	0.124	0.93**	-0.32	1.25***	0.66**	0.01	0.66**
						[2.41]	[-0.71]	[3.69]	[2.06]	[0.03]	[2.52]
Overvalued ($RMV_{0.20}$)	172	0.14	2.24	0.844	0.129	1.10***	0.19	0.91***	0.90***	0.32	0.58***
						[3.47]	[0.48]	[3.28]	[3.34]	[1.19]	[2.59]
Normal (RMV_{normal})	279	0.18	2.22	0.897	0.174	1.15**	1.34***	-0.19	1.15***	1.05***	0.10
						[2.53]	[3.42]	[-0.61]	[3.27]	[3.35]	[0.43]
Undervalued ($RMV_{0.80}$)	149	0.24	2.37	0.957	0.193	2.36***	0.49	1.87***	2.71***	1.05**	1.66***
						[3.29]	[0.78]	[4.03]	[4.24]	[2.22]	[4.70]
Undervalued ($RMV_{0.90}$)	92	0.26	2.41	0.962	0.208	3.22***	0.31	2.91***	3.15***	1.02*	2.13***
						[3.03]	[0.34]	[4.74]	[3.57]	[1.73]	[4.35]
Undervalued ($RMV_{0.95}$)	53	0.28	2.39	0.964	0.211	3.49**	0.67	2.82***	3.54***	1.20	2.34***
						[2.19]	[0.53]	[2.66]	[2.71]	[1.40]	[3.00]

Table IA3

Market-wide Misvaluation and the Value Premium (value-weighted)

This table reports monthly value-weighted returns (in %) of value stocks (V), growth stocks (G) and the value premium under scenarios with different degree of market-wide misvaluation (RMV). At the end of each month, we sort stocks listed on NYSE, NASDAQ and AMEX by their B/M ratios. The top decile is defined as value stocks, while the bottom decile is defined as growth stocks. We report the number of months under different scenarios of RMV, the market-wide B/M, the value spread, the average monthly return of portfolios V, G, and VmG over the next 1 month and the next 12 months. Under *Stock-level Misvaluation* we report the breakpoint ranking of value and growth stocks' valuations relative to the historical benchmark. Newey-West t-statistics are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1968-2018.

				Stock-level Misvaluation		1 month			12 months		
condition	N	Market B/M	Value spread	V	G	V	G	VmG	V	G	VmG
Overvalued ($RMV_{0.05}$)	85	0.54	2.05	0.737	0.106	1.27***	-0.47	1.73***	0.73**	0.49	0.23
						[2.68]	[-0.97]	[3.03]	[2.32]	[1.38]	[0.45]
Overvalued ($RMV_{0.10}$)	129	0.55	2.07	0.730	0.104	1.20***	0.05	1.15**	0.93***	0.79**	0.15
						[3.11]	[0.12]	[2.43]	[3.22]	[2.52]	[0.36]
Overvalued ($RMV_{0.20}$)	195	0.59	2.06	0.735	0.109	1.25***	0.62*	0.63	0.96***	0.93***	0.03
						[4.18]	[1.85]	[1.61]	[3.82]	[3.34]	[0.10]
Normal (RMV_{normal})	285	0.79	2.12	0.812	0.132	1.03**	1.37***	-0.34	1.11***	1.03***	0.08
						[2.44]	[4.70]	[-0.89]	[3.44]	[4.22]	[0.29]
Undervalued ($RMV_{0.80}$)	120	1.18	2.41	0.928	0.153	2.17**	0.01	2.16**	2.24***	0.40	1.84***
						[1.99]	[0.01]	[2.53]	[3.27]	[0.78]	[3.66]
Undervalued ($RMV_{0.90}$)	91	1.26	2.43	0.938	0.163	2.65**	0.03	2.62***	2.37***	0.33	2.04***
						[2.18]	[0.04]	[2.70]	[2.78]	[0.56]	[3.69]
Undervalued ($RMV_{0.95}$)	67	1.29	2.44	0.943	0.167	3.49**	0.29	3.20***	2.48**	0.34	2.14***
						[2.52]	[0.35]	[2.99]	[2.51]	[0.48]	[3.40]

Table IA4

Market-wide Misvaluation and Predictability of Value Premium (value-weighted)

This table reports the coefficient estimates of the following monthly time-series regression:

$$Value\,premium_{t,t+h} = a_0 + a_1 * DOM_t + a_2 * Value\,spread_t + a_3 * X_t + \epsilon_{t,t+h}.$$

The dependent variable is the value-weighted h-month cumulative return of the value-minus-growth strategy, where h=3,6,12. DOM is defined as $(RMV - 0.5)^2$. $Value\,spread$ is the difference between the log B/M of Decile 5 and 1 portfolios, sorted by B/M, after controlling for size. The control variables, X, include the Sentiment Index of Baker and Wurgler (2006), the NBER recession dummy, the equal-weighted average of individual B/M ratios, the lagged risk-free rate, term spread, default spread, the aggregate dividend yield, and market return volatility. Market return volatility is the volatility of daily CRSP equal-weighted returns over the previous 3 months. Newey-West t-statistics are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1968-2018.

$DOM = (RMV - 0.5)^2$									
Coefficient	h=3			h=6			h=12		
a0	-0.74**	-5.56**	-10.72***	-0.58**	-5.88***	-10.82***	-0.15	-6.05***	-11.68***
	[-2.13]	[-1.97]	[-3.30]	[-2.04]	[-2.61]	[-4.17]	[-0.64]	[-4.01]	[-5.90]
a1	10.09***	8.93***	9.52***	8.70***	7.43***	8.29***	5.22***	3.80**	4.47***
	[3.41]	[3.31]	[3.81]	[3.66]	[3.37]	[4.33]	[2.85]	[2.23]	[3.19]
a2		2.30*	2.48*		2.52**	2.58**		2.81***	3.63***
		[1.72]	[1.76]		[2.36]	[2.19]		[3.88]	[3.99]
Adj. R^2	0.04	0.07	0.16	0.07	0.12	0.30	0.04	0.19	0.42
Controls	N	N	Y	N	N	Y	N	N	Y

Table IA5

Market-wide Misvaluation (Alternative Measure RMV^{mwz}) and the Value Premium

This table reports monthly equal-weighted returns (in %) for value stocks (V), growth stocks (G), and the value premium (VmG) under different scenarios of market-wide misvaluation, as measured by RMV^{mwz}. At the end of each month, we sort stocks listed on NYSE, NASDAQ and AMEX by B/M. The top decile is defined as value stocks, while the bottom decile is defined as growth stocks. We report the number of months under different valuation scenarios, the market-wide B/M (the cross-sectional average of individual stock B/M ratios), the value spread, the average monthly return of portfolios V, G, and VmG over the next 1 month and the next 12 months. Under *Stock-level Misvaluation* we report the breakpoint ranking of value and growth stocks' valuations relative to the historical benchmark. Newey-West t-statistics are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1968-2018.

				Stock-level Misvaluation		1 month			12 months		
condition	N	Market B/M	Value spread	V	G	V	G	VmG	V	G	VmG
Overvalued ($RMV_{0.01}^{mwz-}$)	86	0.64	2.05	0.771	0.110	1.01*	-1.44**	2.45***	0.49	-0.89**	1.38***
						[1.65]	[-1.96]	[6.08]	[1.42]	[-2.16]	[4.20]
Overvalued ($RMV_{0.05}^{mwz-}$)	179	0.63	2.06	0.749	0.112	1.20***	0.36	0.84***	1.10***	0.28	0.82***
						[3.66]	[1.04]	[3.11]	[3.80]	[1.07]	[3.64]
Overvalued ($RMV_{0.10}^{mwz-}$)	234	0.62	2.07	0.746	0.113	0.95**	0.02	0.93***	0.97***	0.00	0.98***
						[2.47]	[0.05]	[2.82]	[3.21]	[-0.01]	[3.79]
Normal (RMV_{normal}^{mwz})	233	0.75	2.18	0.806	0.122	1.53***	1.24**	0.29	1.57***	0.90**	0.67***
						[3.21]	[2.23]	[0.83]	[4.65]	[2.47]	[2.70]
Undervalued ($RMV_{0.10}^{mwz+}$)	133	1.20	2.27	0.922	0.170	3.12***	0.48	2.65***	3.37***	1.02*	2.34***
						[3.03]	[0.68]	[3.96]	[4.08]	[1.80]	[4.52]
Undervalued ($RMV_{0.05}^{mwz+}$)	118	1.23	2.29	0.929	0.172	2.43***	0.99	1.44**	2.80***	1.07***	1.73***
						[3.51]	[1.59]	[2.39]	[5.25]	[2.58]	[4.51]
Undervalued ($RMV_{0.01}^{mwz+}$)	78	1.32	2.28	0.943	0.186	3.85***	0.53	3.32***	4.31***	1.32**	3.00***
						[2.70]	[0.62]	[3.57]	[3.80]	[1.91]	[4.09]

Table IA6

Market-Wide Misvaluation (Alternative Measure RMV^{mwz}) and Predictability of the Value Premium

This table reports the coefficient estimates of the following monthly time-series regression:

$$Value\,premium_{t,t+h} = a_0 + a_1 * DOM_t + a_2 * Value\,spread_t + a_3 * X_t + \epsilon_{t,t+h}.$$

The dependent variable is the equal-weighted h-month cumulative return of the value-minus-growth strategy, where h=3,6,12. DOM is defined as $|RMV^{mwz}|$. $Value\,spread$ is the difference between the log B/M of value and growth stocks. The control variables, X, include the Sentiment Index of Baker and Wurgler (2006), the NBER recession dummy, the equal-weighted average of individual B/M ratios, the lagged risk-free rate, term spread, default spread, the aggregate dividend yield, and market return volatility. Market return volatility is the volatility of daily CRSP equal-weighted returns over the previous 3 months. Newey-West t-statistics are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 1968-2018.

$DOM = \|RMV^{mwz}\|$									
Coefficient	h=3			h=6			h=12		
a0	-0.26	-7.15***	-7.06***	-0.13	-6.57***	-6.64***	0.30	-5.63***	-6.54***
	[-0.68]	[-3.03]	[-2.79]	[-0.41]	[-3.48]	[-3.41]	[1.29]	[-4.99]	[-5.38]
a1	0.80***	0.82***	0.67***	0.69***	0.71***	0.54***	0.47***	0.49***	0.33***
	[3.62]	[3.88]	[4.22]	[3.68]	[4.06]	[4.54]	[3.65]	[4.32]	[4.46]
a2		3.18***	1.59		2.97***	1.23		2.73***	1.85***
		[2.93]	[1.44]		[3.48]	[1.45]		[5.44]	[3.49]
Adj. R^2	0.11	0.17	0.24	0.15	0.24	0.40	0.13	0.31	0.50
Controls	N	N	Y	N	N	Y	N	N	Y